APPLICATION OF NEURAL NETWORK IN FINANCIAL MARKET

by

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Certification

I hereby declare that this submission is my own work towards the MPhil and that, to the best of my knowledge, it contains no material previously published by another person nor material which has been accepted for the award of any other degree of the University, except where due acknowledgement has been made in the text.

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Abstract

To be successful in a competitive world, any organization must not only maintain a good understanding of the current conditions, but be able to forecast the future as accurately and precisely as possible. Analysis of historical trends in data, with a view to making predictions is therefore a key task, and one for which neural network technology is well suited. In general, application of neural network in financial market is discussed. Specifically, the prediction of foreign exchange rate using neural network called "feedforward" neural network with one hidden layer consisting of three neurons is considered in deriving the model for the forecasting. Statistical evaluation of the output from the implementation of the neural network model on the forecast values with the actual of Banks-Indicative Opening U.S. Dollar, Pound Sterling and Euro Rates – Selling, are discussed. Further comparison of the results obtained from the improved model and the existing model was considered. The results obtained suggest that neural network model produces better accurate predictions than other time series forecasting models. The use of the system in financial market and specifically on the prediction of exchange rates typically involves the utilization of other financial indicators and domain knowledge since real life data were used as input.

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CHAPTER ONE: GENERAL INTRODUCTION

1.0 Background of the Study

As the world economy keeps on changing, financial institutions and investors always look forward to a system by which they can monitor the dynamic financial state of the world. This calls for a system that could simulate and predict financial positions based on financial market trends in order to manage and identify the best package to invest in. This calls for application of artificial neural network. An Artificial Neural Network is a network of many very simple processors ("units"), each possibly having a (small amount of) local memory. The units are connected by unidirectional communication channels ("connections"), which carry numeric (as opposed to symbolic) data. The units operate only on their local data and on the inputs they receive via the connections. The design motivation is what distinguishes neural networks from other mathematical techniques: A neural network is a processing device, either an **algorithm**, or **actual hardware**, whose design was motivated by the design and functioning of human brains and components thereof [1].

Managing financial securities requires seeing through future trends in financial market. An artificial neural network is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase to make time series prediction. Neural networks are non-linear statistical data modeling tools or information processing paradigm that have remarkable ability to derive meaning from complicated or imprecise data. This unique ability has made it possible for Artificial Neural Network (ANN) to be employed to extract patterns and also detect trends that are very complex to be noticed by either humans or other forms of computer techniques.

They can be used to model complex relationships between inputs and outputs or to find patterns in data.

The question is, though, if neural networks can be used to predict trends in data that humans might not notice, and successfully use these trends in their predictions, will it not be a good tool to use in financial management? Their simple implementation and the existence of mostly local dependencies exhibited in the structure of financial management allows for fast, and parallel implementations in hardware.

Financial management involves a system of collection and presentation of relevant economic information relating to an enterprise for planning, controlling and decision making.

Financial Management financial management encompasses the core processes of resources management and finance operations. This concentrates on controlling the financial market trend – having power over the declining trend of market prices. It is the planning, managing and controlling financial resources to maximize shareholders value.

Managing the Ghanaian market requires controlling the financial market trends which is directly related to how the cedi compete with the foreign currencies.

Approaches to forecasting the future values of exchange rates fall broadly into two categories - those that rely on *technical analysis*, and those that rely on *fundamental analysis*. While technical analysis uses only historical data (past prices, volume of trading, volatility, etc.) to determine the movement in the price of some financial commodities, fundamental analysis is based on external information; that is, information that comes from the economic system surrounding the market [2].

In Ghanaian market such information includes import rates, prices of the imported goods and services and many other macro- or micro-economic variables which have strong correlation to the exchange rates.

The importance of exchange rate forecasting in Ghana include the benefit of exchange rate stability derived by Central Bank, the ability of Financial Institutions to trade in currency market and attraction of Foreign Institutional Investors and Corporate firms cannot be undermined.

It is upon this background that there is the need for a study of the application of neural network in financial market with emphasis on exchange rate predictions. This will help to come out with the better plans to curb problems that are associated with individuals and the financial institutions with special reference to managing the trends in financial market.

1.1 Statement of Problem

The knowledge of future values of exchange rates is a keen issue in financial market. This is because the cost of import and export of goods or services is highly dependent on how a currency trades in the international market. It has been the model of the financial institutions, corporate bodies, individuals and the government to use the available resources, the interbank exchange rates, in their unilateral role. This does not make them efficient in projecting financial market to a point where investors will be confident to risk highly since proper management is not in place.

People have the interest in making investment such as purchasing shares and treasury bills but their fear is whether their investment will be profitable or incur a loss. Since financial institutions are unable to forecast the financial market trends. It is difficult to predict the elements of financial markets such as bond price which is critically dependent on exchange rates.

These financial securities cannot be properly managed without the knowledge of how our local currency trades in the international market. This is because these financial securities depend on the foreign currencies and how our local currency fair with them. Thus, are artificial neural networks superior to simple linear modeling techniques in forecasting foreign exchange rates?

Since ANNs are best at identifying patterns and trends in data, they are well suited for forecasting or predictions such as future values of foreign exchange rates.

1.2 Research Objective

The research objective is classified into general and specific objectives.

General Objective: In general the question as to "how neural network can be applied to financial management, to forecast foreign exchange rates? is what this research aim at answering.

Specific Objectives: Specifically, this research will try to ascertain:

- how neural network function and its application to financial market?
- how will the efficiency of the application in financial market to predict foreign exchange rates aid in managing financial market?
- a model to help make contingency plans to forestall uncertainties in financial market for example global economic crisis.
- dependency of foreign exchange rates on financial market in artificial trading.
- simulation model for teaching purposes.

1.3 Significance of the Study

The main significant bedrock of this research is to aid in obtaining future values of exchange rate which is a key factor in monitoring financial market trends. For instance, financial institutions who invest in foreign securities will be able to do artificial trading if they are able to forecast the rate at which the local currency will be faring in future times. Businesses will be able to foresee prices of commodities at some point in time in the future based on the predictions of the exchange rates in the world market. This research is expected to obtain fundamental as well as highly developed principles to promote the significance of having suitable application of neural network in financial management of the financial institutions in Ghana to forecast and predict financial market trends.

This will mainly help companies to forecast the trends in financial market in order to see how successful they are in sustaining interest value. This will in turn assist investors to know the financial market trends and the best investment package to depend on. It will also aid the management of companies to monitor the performance of company's financial market trends.

The government will be able to make contingency plans to control the inflow and outflow of funds to prevent unexpected economic crisis.

The utilization of neural network models lies in the fact that they can be used to infer a function from observations.

The tasks to which neural networks are applied tend to fall within the following broad categories:

- Function approximation, or regression analysis, including time series prediction and modeling.
- Classification, including pattern and sequence recognition, novelty detection and sequential decision making, decision processing or target marketing.
- Data processing, including filtering, clustering, blind source separation and compression, navigation, disease recognition, text recognition and game playing.

From the scope of applications, it is clear that considerable work has been done in the field of ANN deployment. Nevertheless, the application of neural network in financial market in Ghana to predict foreign exchange rates cannot be overemphasized.

1.4 Scope and Limitation of the Study

This research puts into consideration the forecast of financial market trends with specific reference to the carious prediction of future foreign exchange rates based on previous observations of interbank exchange rates.

It is expedient to apply the model developed in this research to all financial market trends of all the financial securities such as bonds, treasury bills and shares but since these securities depend mainly on trading with the foreign currencies the emphasis is on only the forecast of foreign exchange rates.

There are many application areas of neural networks which include system identification and control (vehicle control, process control), game-playing and decision making (backgammon, chess, racing), pattern recognition (radar systems, face identification, object recognition and more), sequence recognition (gesture, speech, handwritten text recognition), medical diagnosis, financial applications (automated trading systems), data mining (or knowledge discovery in databases), visualization and e-mail spam filtering.

With all these applications, this research is limited to the application of neural networks concentrating on managing the financial market trends with specific emphasis on forecasting the exchange rate.

1.5 Organization of the Study

The study is organized as follows:

The first chapter entails the general introduction, which deals with the background of the study, statement of the problem, research objectives (both general and specific), significance of the study, scope and limitations of the study, definition of terms and organization of the chapters.

The second chapter involves a literature review on neural networks and financial management. This gives detailed information of some existing forms of applications of neural networks in financial management.

The third chapter presents the methodology of the study, pointing out the various instruments used in data collection and their description which includes the analysis of input, processing and output on the functionalities of the neural networks. The design of the proposed system will be outlined.

The fourth chapter focuses on the implementation of neural network in financial market relating to the research objectives.

Chapter five which is the last chapter, deals with the conclusion and recommendation of the research paper as well as future possible applications of neural networks in financial market.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

One of the most important features of a neural network is its ability to adapt to new environments. Therefore, learning algorithms are critical to the study of neural networks. There are many different types of Neural Networks, each of which has different strengths particular to their applications. The abilities of different networks can be related to their **structure**, **dynamics** and **learning methods**. Neural Networks offer improved performance over conventional technologies in areas which includes: **Machine Vision**, **Robust Pattern Detection**, **Signal Filtering**, **Virtual Reality, Data Segmentation**, **Data Compression**, **Data Mining**, **Text Mining,** **Artificial Life**, **Adaptive Control**, **Optimisation** and **Scheduling**, **Complex Mapping** and more [3].

It is natural and informative to judge forecasts by their accuracy. However, actual and forecasted values will differ, even for very good forecasts. To take an extreme example, consider a zeromean white noise process. The optimal linear forecast under quadratic loss is simply zero, so the paths of forecasts and realizations will look different. These differences illustrate the inherent limits to predictability, even when using optimal forecasts. The extent of a series' predictability depends on how much information the past conveys regarding future values of this series; as a result, some processes are inherently easy to forecast, and others are difficult. In addition to being of interest to forecasters, predictability measures are potentially useful in empirical macroeconomics. Predictability provides a succinct measure of a key aspect of time series dynamics and is therefore useful for summarizing and comparing the behavior of economic series, as well as for assessing agreement between economic models and data [4].

Diebold and Kilian [6], do not advocate comparing models to data *purely* on the basis of predictability. Rather, predictability simply provides an easily-digested summary distillation of certain important aspects of dynamics. Remarkably little attention has been paid to methods for measuring predictability.

Existing methods include those based on canonical correlations between past and future, and those based on comparing the innovation variance and unconditional variance of stationary series [7][8]. Those methods, however, are inadequate in light of recent work stressing the possible presence of unit roots, rich and high-dimensional information sets, non-quadratic and possibly even asymmetric loss functions, and variations in forecast accuracy across horizons [9]. It has been realized that the major forecasting methods used in the financial area are either technical or fundamental. Due to the fact that stock markets are affected by many highly interrelated economic, political and even psychological factors, interactions among these indicators become very complex. Therefore, it is generally very difficult to forecast the trend in the stock market. Classical statistical techniques for forecasting reach their limitation in applications with nonlinearities in the data set [10]. There are quite a number of applications of neural network and this paper attempts to give references and disparate list of demos on real life applications, those that comes with video clips on the internet. The applications featured here are:

- CoEvolution of Neural Networks for Control of Pursuit & Evasion
- Learning the Distribution of Object Trajectories for Event Recognition
- Radiosity for Virtual Reality Systems
- Autonomous Walker & Swimming Eel
- Robocup: Robot World Cup

- Using HMM's for Audio-to-Visual Conversion
- Artificial Life: Galapagos
- Speechreading (Lipreading)
- Detection and Tracking of Moving Targets
- Real-time Target Identification for Security Applications
- Facial Animation
- Behavioral Animation and Evolution of Behavior
- A Three Layer Feedforward Neural Network
- Artificial Life for Graphics, Animation, Multimedia, and Virtual Reality: Siggraph '95 Showcase
- Creatures: The World Most Advanced Artificial Life!
- Framsticks Artificial Life

All these present practical applications of neural network, real life applications as well as abstract and future applications [3].

In relation to this study, thus application of neural network in financial market, a review of how neural network has been implemented in predicting financial market trends and also the use of neural network in time series predictions are presented.

Considering these practical applications of neural network on the internet, it is clear that in the system that illustrates behaviour generated by dynamical recurrent neural network controllers (co-evolved for pursuit and evasion capabilities), the time-series are fed into a custom 3-D movie generator. Although the chase behaviors are genuine data, the 3D structures, surface physics, and shading are all purely for illustrative effect.

Also, in order to develop the techniques necessary to build a dynamically stable legged vehicle controlled by a neural network, this had to incorporate command signals, sensory feedback and reflex circuitry in order to produce the desired movement. This in effect made the implementation complex and expensive.

2.2 Reviewed Papers on Application of Neural Network in Financial Market

There has been quite a number of works done on artificial neural network with its application to financial market as well as financial management and some are presented in subsequent sessions.

2.2.1 Time Series Prediction and Neural Networks

Frank R. J., *et al* [9] began by discussing Neural Network approaches to time series prediction, and the need to find the appropriate sample rate and then identified an appropriately sized input window. They proposed that, work in neural networks on forecasting future developments of the time series is from past values of *x* up to the current time. Formally this could be stated as: find a function $f : \Re N \rightarrow \Re$ such as to obtain an estimate of *x* at time t + d, from the N time steps back from time t, so that:

$$x(t+d) = f(x(t), x(t-1), \ldots, x(t-N+1)) \qquad 2.1$$

$$x(t+d) = f(\mathbf{y}(t)) \qquad 2.2$$

where $\mathbf{y}(t)$ is the N- ary vector of lagged *x* values

Normally *d* will be one, so that *f* will be forecasting the next value of *x*.

They trained a feedforward neural network with 120 hidden units, using conjugate gradient error minimization. The embedding dimension, the size of the input layer, is increased from 1 unit to 9 units. The data is split into a training set of 1200 vectors and test set of 715 vectors. Each network configuration is trained 10 times with different random starting points.

It can be inferred from Frank R. J., *et al*. [9] findings that the results they obtained by testing the model with the data set suggested that the embedding theorem and the false nearest neighbour method can provide useful heuristics for use in the design of neural networks for time series prediction. With two of the data sets they examined here, the predicted embedding size corresponded with a network configuration that performed well, with economical resources. On the other hand, in their research and with reference to their data sets they did not observe an overlarge embedding size to have a deleterious effect on the network. The tree ring data, however, showed that conclusions must be treated with caution, since poor predictive results were produced whatever the window size.

2.2.2 Traffic Trends Analysis using Neural Networks

According to Edwards T., *et al*. [10], one aspect of time series analysis involves forecasting the value of a variable from a series of observations of that variable up to a particular time. They suppose that observations are available at discrete, equispaced historical time intervals, $z[T]$, $z[T-\tau]$, $z[T-2\tau]$, $z[T-3\tau]$…, with time interval τ. The observations $\{z(T), ... z[t - (N-1)\tau]\}$ constitute a "window" and N is referred to as the window size. The aim is to forecast the value of z at some later time, $z_f(T+L)$, where L is the lead-time and is an integral multiple of τ. More formally the objective is to obtain a forecast function $z_f(T+L)$ which minimises the mean square of the deviations $z_f(T+L)$ - $z(T+L)$ for each lead time L.

They proposed that the simplest way to estimate z_f using a neural net is to use a feedforward net with one input for each member of the window and one output for z_f(N+ t). An obvious extension of this model is to have multiple outputs corresponding to multiple lead times. These models are often called sliding window nets. As such, a more sophisticated predictor may be produced by buffering either the hidden units or the output units and recurrently adding these activations to the input vector. These predictors are particularly useful when the data is inherently noisy. In the work reported here they used a single hidden layer feedforward net with a sliding window input, trained with a scaled conjugate gradient algorithm.

They concluded that, Neural Networks provide a useful tool for time series prediction in the telecoms domain. Critical to the performance of the predictor is the selection of an appropriate window size for the data which needed to be modeled. The nearest neighbor algorithm, which they described, has been tested empirically and shown to be a valuable technique for allowing definition of this window size from analysis of the data.

2.2.3 Neural Networks, Financial Trading and the Efficient Markets Hypothesis

Skabar and Cloete [11] here described a methodology by which neural networks can be trained indirectly, using a genetic algorithm based weight optimization procedure, to determine buy and sell points for financial commodities traded on a stock exchange. In order to test the significance of the returns achieved using this methodology, the returns on four financial price series were compared with returns achieved on random walk data derived from each of these series using a bootstrapping procedure. These bootstrapped samples contain the same distribution of daily returns as the original series, but lack any serial dependence which is present in the original. The results indicated that on the Dow Jones Industrial Average Index, the return achieved over a four year out of sample period were significantly greater than that which would be expected had the price series been random. This lends support to the claim that some financial time series are not entirely random, and that – contrary to the predictions of the efficient markets hypothesis – a trading strategy based solely on historical price data can be used to achieve returns better than those achieved using a buy-and-hold strategy.

2.2.4 An Empirical Analysis of Data Requirements for Financial Forecasting with Neural Networks

Walczak [12] makes it clear that evidence has been presented that contradicts the current financial neural network development heuristic, which implies that greater quantities of training data is necessary to produce better-quality forecasting models. A new time series model, termed the Time-Series Recency Effect, has been demonstrated to work consistently across neural network models for six different currency exchange time series. The Time-Series Recency Effect claims that model building data that is nearer in time to the out-of-sample values to be forecast produces more accurate forecasting models.

The empirical results discussed in this article show that frequently a smaller quantity of training data will produce a better-performing backpropagation neural network model of a financial time series. Other problematic issues related to the development of the best possible neural network model such as selection of input variables or selection of the neural network training algorithm and the design of the neural network architecture are not discussed in the literature. The prudent financial time series neural network developer will realize that these other factors will affect the neural network model's performance and should utilize existing guidelines to solve these issues. He then pointed out that for financial time series two years of training data is frequently all that is required to produce optimal forecasting accuracy.

He further proposed that future research can continue to provide evidence for the Time-Series Recency Effect by examining the effect of training set size for additional financial time series (e.g., any other stock or commodity and any other index value). The Time-Series Recency Effect may not be limited only to financial time series, and evidence from nonfinancial time series domain neural network implementations already indicates that smaller quantities of more recent modeling data are capable of producing high-performance forecasting models. Additionally, the Time-Series Recency Effect has been demonstrated with neural network models trained using backpropagation.

In summary, it has been noted that neural network systems incur costs from training data. This cost is not only financial, but also impacts the development time and effort. Empirical evidence demonstrates that frequently only one or two years of training data will produce the "best" performing backpropagation trained neural network forecasting models. The proposed methodology for identifying the minimum necessary training set size for optimal performance enables neural network researchers and implementers to develop the highest-quality financial time series forecasting models in the shortest amount of time and at the lowest cost.

2.2.5 Neural Network and Equity Forecasting

Jingao and Hean-Lee [13], carried out a research on the performance of several backpropagation neural networks applied to the prediction of Kuala Lumpur Stock Exchange Composite Index (KLSE) on stock market index. The delayed index levels and some technical indicators were used as the inputs of neural networks, while the current index level was used as output. With the prediction, significant paper profits were obtained for a chosen testing period of 304 trading days in 1990/91. Besides, the experiments showed that useful prediction could be made without the use of extensive market data or knowledge. They pointed out four challenges beyond the choice of either technical or fundamental data for using neural network to forecast the stock prices. First, the inputs and outputs of the neural networks have to be determined and preprocessed. Second, the types of neural networks and the activation functions for each node have to be chosen. Third, the neural network architecture based on the experiment with different models has to be determined. Finally, different measures to evaluate the quality of trained neural networks for forecasting have to be experimented with.

2.2.6 A Prediction Analysis on Hong-Kong Hang Seng Indices Using Neural Networks

In the paper by Lam and Tong [14] on A Prediction Analysis on Hong-Kong Hang Seng Indices using neural network, they based their model on prediction algorithm for the stock market. A basis of this algorithm is a net computation in artificial neural network system theory. They give a summary of the theory of neural network system and some of its recent developments, such as: basic properties of perceptron and its dynamical indices; generalizations of the perceptron model and their learning rules.

In their construction of a prediction model of the stock market according to the net computation theory, they determined their model by the following steps:

1. A data flow of the stock market quotations was defined by

$$\mathcal{X}(s) = (\mathcal{X}_1(s), \ldots, \mathcal{X}_k(s)),\ s = \ldots, -1, 0, 1, 2, \ldots, \qquad 2.3$$

   where $\mathcal{X}_i(s)$ is i-th index at time s of a stock market, those indices refer to some data of stock market quotations, such as the opening price

2. Their prediction objective is said to be a up-down objective and the prediction problem is said to be a up-down problem. In general, a prediction objective is a vector:

$$\mathcal{U}_l(s) = \mathcal{U}_l\,[(\mathcal{X}_1(s-1), \mathcal{X}(s-2), \ldots, \mathcal{X}(s-2)],\ l = 1, \ldots, L. \qquad 2.4$$

   Since $\mathcal{U}_l$ is an estimation, the prediction model is similar to a statistical prediction model, but their study is in the framework of neural network system theory.

3. They continue to give a prediction model of net computation which is defined by

$$\mathcal{U}_l = \text{Sgn}\{\textstyle\sum_{i=1}^{n} \sum_{j=1}^{k} \boldsymbol{w}_{l;i,j}\,(t)\boldsymbol{x}_j\,(t-i)\},\ l = 1, \ldots, L. \qquad 2.5$$

4. They finally construct the learning objective of net computation for the prediction of stock market.

$$\mathcal{U}_l(t) = \text{Sgn}\{\textstyle\sum_{i=1}^{n} \sum_{j=1}^{k} \boldsymbol{w}_{l;i,j}\,(t)\boldsymbol{x}_j\,(t_i)\},\ l = 1, \ldots, L. \qquad 2.6$$

They therefore, concluded from their result that the stock markets are volatile everywhere in the world, but the Hang Seng Index (HSI) in Hong Kong is exceptionally so as is evident from their results. In just 3 years, from 90.1.3 to 92.12.28, the HSI almost doubled from 2,838 to 5,532. This, they said is equivalent to an average daily increase of 3.54 index point.

This model, though successful in classifying certain patterns has a limitation of solving problems related to classic XOR (exclusive or). This is because their neural network model can be considered as analogous to non-linear, non-parametric regression which means they make no assumption about the distribution of the data, and instead allow the data to speak for itself.

2.2.7 Neural Networks for Time Series Forecasting: Practical Implications of Theoretical Results

The research work done by Thielbar and Dickey [15] on "Practical Implications of Theoretical Results; Neural Networks for Time Series Forecasting" begin by arguing that research on the performance of neural networks in modeling nonlinear time series has produced mixed results. In addition, they state that while neural networks have great potential because of their status as universal approximators, their exibility can lead to estimation problems [15].

They continued by deriving some theoretical properties of an AR-NN with one lag and then shift to simulate results and focus on an autoregressive neural network model with one lag and one hidden unit, where the noise term is distributed as N(0; 1).

After comparing the various models reviewed by Thielbar and Dikey the simplest case of an autoregressive neural network model was proposed. This model has one hidden unit given as ($\lambda tanh(Y(Y_{t-1} - c))$) and one shortcut connection given as ($\alpha_1 Y_{t-1}$). They then used the hyperbolic tangent function tanh(.) as the activation function, since they deemed it convenient for their purposes.

They continue to state that all moments of the noise term exist, and as long as the autoregressive portion (Y_t – α_0 - $\alpha_1 Y_{t-1}$) is stationary, the mean, μ_y, exists. Taking expectations of both sides and rearranging gives μ_Y as a function of the parameters and the expectation of the hyperbolic tangent function.

After analyzing the various parameters involved they came out with the model equation as:

$$Y_t = \alpha_0 + \rho y_{t-1} + \lambda \tanh\left(Y(y_{t-1} - c)\right) \quad 2.7$$

It comes into view that unreasonable parameter values are possible, even when the architecture of the AR-NN is known and the true parameter values are used as starting values for the nonlinear model. In our simulation, the unreasonable parameter estimates occurred for 3% of the cases and not consistently for any parameter combination. For this reason these series were dropped before calculating Y_{t-1} statistics. The forecasts were generated in one of two ways:

1. A point forecast, where the last lag (y_{t-1}) is used to predict the next value in the sequence (y_t). The function is then updated with the true value for the next period's forecast.

2. A bootstrap forecast, where at each point 500 different values for y_{t-1} are generated from the assumed distribution, and the forecast is an average of the forecasts from these generated values.

In their conclusion, it was pointed out that for simulation; this model allows limiting the design space due to the bounded nature of the activation function. But for practical applications, they can use the theoretical limits as a guide in selecting starting values for the simulation.

Also the location of the neural network attraction point(s) is important in determining long-run behavior of the network. If the attraction point is such that the generated data are not near the location parameter(s) for the activation function, it is possible for the series data to cluster in a location where there is little information about the parameters of the nonlinear model.

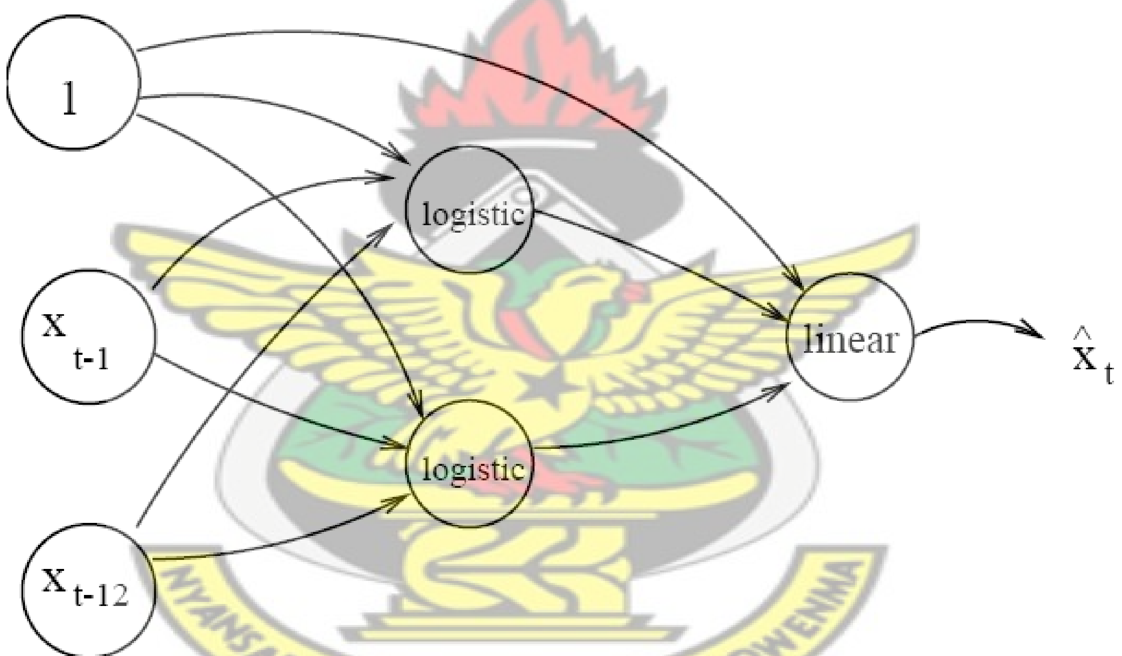
It was realized that even the general properties derived hold for their simple model, and that even when the AR-NN is reduced to its simplest form, the practical aspects of model estimation can still cause problems in using an AR-NN to forecast a nonlinear time series.

2.2.8 Time Series Forecasting with Neural Networks: A Comparative Study using the Airline Data

A time series forecast modeled by Faraway and Chartfield [17] was based on a comparative study of Box-Jenkins approach to forecasting the airline data, which had an upward trend together with seasonal variation whose size is roughly proportional to the local mean level and hence is said to be multiplicative. And also Holt-Winter's exponential smoothing model was based on standard analysis which generally incorporates taking a logarithmic transformation of the data in order to make the seasonal effect additive, and then taking one seasonal and one non-seasonal difference in order to make the series stationary. One seasonal and one non-seasonal moving averages terms were then fitted [17].

Upon comparison Faraway and Chartfield deduced their neural network model on a general premises by regarding Holt-Winter's exponential smoothing as being the most suitable for this particular set of data (airline data), though many other seasonal models could be fitted which gives measures of fit and forecast accuracy nearly as good as those for the airline model [17].

A neural network architecture for forecasting airline data as modeled by Faraway and Chartfield is shown in Figure 2.0.



Input layer Hidden layer Output layer

Figure 2.0: A one hidden layer of 2 neurons neural network architecture for forecasting modeled by Faraway and Chartfield

Deriving the forecast equation, they first introduce a linear function of the inputs as

$$\sum_{\mathrm{i}-1}^{3} w_{ij}\ y_i \qquad 2.8$$

where w_{ij} denotes the rate of the connection between input y_i and the jth neuron. The values of the inputs under consideration are y_1 = unity, $y_2 = x_{t-1}$ and $y_3 = x_{t-12}$. The linear sum, say v_j, is then transformed by applying a function called a *logistic activation function*, as in equation 2.9

$$z_j = 1/(1 + e^{-vj}) \qquad 2.9$$

and which gives values in the range of zero(0) and one(1). In the example, this leads to values z_1 and z_2 for the two neurons. A similar operation could then be applied to the values of z_1, z_2 and the constant input in order to get the predicted output. A linear function of the neuron values is typically used as the activation function at the output stage and is just the identity function. [17]

For a neural network model with one hidden layer, the general prediction equation for computing a forecast of x_t (the output) using selected past observations, x_{t-j1};. . . ;x_{t-jk} as the inputs, they propounded the form:

$$\hat{x}_t = \emptyset_o(w_{co} + \sum_h w_{ho}\emptyset_h(w_{ch} + \sum_i w_{ih}\, x_{t-ji})) \qquad 2.10$$

Upon forecasting using the model by Faraway and Chatfield, two practical problems were encountered. Firstly, the untransformed airline data lied in the range of 104 to 622, hence the starting values used in the algorithm were out of scale with the input values and that the fitting algorithm failed to converge in a sensible way. Thus they were required to rescale the airline data by dividing by 1000. But it was realized that the problem will arise when the series exceed 1000 which is possible with time. The default choice of the activation function at the output stage is the logistic function, but this constraints the output or the forecast values of categorical data to be in the range of zero(0) and one (1) [17].

2.3 Reviewed Papers on Application of Neural Network in Exchange Rate Predictions

Artificial Neural Network (ANN) has been found to be a good tool for nonlinear statistical techniques that have remarkable ability to derive meaning from complicated or imprecise data. Considerable number of work has been done on its application for predicting currency exchange rates. Since ANN are well suited for forecasting or prediction of exchange rates, this research is aimed at applying it to the prediction of the exchange rates of the Ghanaian cedi with the foreign currencies. This section therefore, considers review of some papers on application of neural network for forecasting exchange rates.

2.3.1 Forecasting Exchange Rates Using Neural Networks for Technical Trading Rules

Philip and van Griensven [18], examine the performance of artificial neural networks (ANNs) for technical trading rules for forecasting daily exchange rates.

With the formulation of their forecasting model, they denoted the exchange rate as y_t , where t is a daily index, and then define the return on the exchange rate as $r_t = \log y_t - \log y_{t-1}$. Considering the moving average $m_t(n)$ when it is defined as:

$$m_t(n) = n^{-1} \sum_{i=0}^{n-1} \mathrm{y}_{\mathrm{t-1}} \qquad 2.11$$

Clearly, for $n = 1$, $m_t(n)$ equals y_t . Very simple technical trading rules consider the signal $s_t(n_1, n_2)$ defined by:

$$s_t(n_1, n_2) = m_t(n_1) - m_t(n_2), \qquad 2.12$$

where $n_1 < n_2$. When s_t (n_1, n_2) exceeds zero (or some other preset value), the short-term moving average exceeds the long-term moving average to a certain extent, and a "buy" signal is generated. Conversely, when s_t (n_1, n_2) is negative (or below a certain threshold), a "sell" signal is given. For daily data, typical choices in practice are n_1 = 1 or 5, and n_2 = 50, 100, or 150. [18]

If a moving average rule like Equation (2.12) is an explanatory variable for the returns r_t , one may want to consider the linear model as in equation 2.13

$$r_t = \alpha s_{t-1} (n_1, n_2) + \beta + \varepsilon_t , \qquad 2.13$$

where α and β are unknown parameters and ε_t is some kind of error process. A motivation for Equation (2.13) is that when a buy signal is given at $t - 1$, and s_t (n_1, n_2) is a relevant explanatory variable, one would expect that r_t is indeed positive; and when a sell signal is given, r_t should be negative. This already suggests that one may be interested more in the sign of the forecasted r_t in conjunction with the sign of the observed r_t than in the specific values of the forecast errors. The Equation (2.13) was then used as the benchmark model. They chose to use Equation (2.13), especially since it is nested in thier ANN, architecture. This is because theoretically, according to some arguments, Equation (2.13) cannot be an adequate descriptive model. Given the potential usefulness of ANNs, modification of Equation (2.13) resulted as:

$$r_t = \propto s_{t-1}(n1, n2) + \sum_{j=1}^{q} \beta_j G[\gamma_j \; s_{t-1}(n1, n2)] + \varepsilon_t \qquad 2.14$$

with

$$G(a) = (1 + \exp(-a))^{-1}, \qquad 2.15$$

where α and Y_j are unknown parameters for $j = 1, 2, \ldots, q$. This ANN model contains $2q + 1$ parameters and therefore referred to as a feedforward single-hidden-layer neural network with q units in the hidden layer. The function $G(a)$ is taken as the logistic activation function, which connects the q input components with the hidden layer. The hidden layer is connected with the output variable r_t through the β_j parameters. The expression in Equation (2.14) indicates that it allows the intercept in Equation (2.13) to be time varying and to depend on the input variable. This is one of the main features of an ANN modeled by Philip and van Griensven [18].

Upon consideration of the results obtained, it can be inferred that the ANN model performed well, and that they were often better than linear models compared by Philip and van Griensven. This notwithstanding, the precise number of hidden layer units in the model appeared less important for forecasting performance than was the choice of explanatory variables. In addition if more sophisticated trading rules, different sample sizes, and various exchange rates can be considered, will not converge at accurate forecast values and one may need to re-estimate the parameters for every new sample. Also, alternative versions of ANNs, which can pick up even more complicated relations between returns and explanatory variables, can perform better than this.

2.3.2 Forecasting Foreign Exchange Rates Using Recurrent Neural Networks

In order to forecast foreign exchange rates by Tenti [19], he proposed the use of recurrent neural network in which activity patterns pass through the network more than once before generating an output. This can learn extremely complex temporal sequences. They made a comparison of three architectures in terms of prediction accuracy of futures forecast for

Deutche mark currency. They then devised and optimized a trading currency by taking into account transaction costs, shown for the different architectures.

With respect to the derivation of the model for recurrent neural network, the use of an exponential trace memory which acts on the series of input $x(1), \ldots, x(t)$, creating a state representation as $[x_1(t), x_2(t), \ldots, x_i(t)]$. Their model equation for the forecast value $x_i(t)$ is given as:

$$x_i(t) = (1 - \mu_i)\, x_1(t) + \mu_i x_{i(t-1)} \qquad 2.16.$$

This model is then implemented by Tenti with three different recurrent neural network architecture of which the first architecture has one recurrent neurode, the second with two recurrent neurode and the third with three recurrent neurrode. This therefore, allow for incremental calculations of the forecast value [19].

The forecast formulated by the three versions of the recurrent neural networks was just the initial part of the trading strategy according to Tenti. He further transformed the predictions into market actions obtained by specifying a set of rules to buy and sell currency futures.

Although, it is quite significant that Recurrent Neural Networks can yield good results due to the rough repetition of similar patterns present in foreign exchange and other time series forecasting. It is critical to mention that Recurrent Neural Networks require substantially more connections, and more memory in simulation, than standard neural networks. These subtle sequences cannot provide beneficial forecastability.

2.3.3 Forecasting Exchange Rates using Feedforward and Recurrent Neural Network

Chung-Ming and Tung [20], investigated the out-of-sample forecasting ability of feedforward and recurrent neural networks based on empirical foreign exchange rate data. They proposed a two-step procedure to construct suitable networks, in which networks were selected based on the predictive stochastic complexity (PSC) criterion, and the selected networks were estimated using both recursive Newton algorithms and the method of nonlinear least squares.

In establishing their model for forecasting, the discussed two basic tasks in building neural networks: (i) estimation of unknown network parameters of which they stated, minimizes mean squared approximation, and (ii) determination of a suitable network structure which is a criteria for complexity regularization.

They further employed a two-step procedure to construct empirical neural networks. First, settle the activation functions ψ as the logistic function and ϕ as the identity function in the networks equations. These choices are quite standard in the neural network literature. Their dependent variables y were changes of log exchange rates, and for each exchange rate, networks explanatory variables x were own lagged dependent variables [20].

Their results show that PSC is a sensible criterion for selecting networks and for certain exchange rate series, but some selected network models have significant market timing ability and/or significantly lower out-of-sample mean squared prediction error. In effect, this model does not give accurate predictions since the use of random data work well with the model criterion.

2.3.4 Forecasting Foreign Exchange Rates with Artificial Neural Networks: A Review

Huang W., *et al.* [21], presented a survey of forecasting exchange rates using artificial neural networks. According to them, several design factors significantly impact the accuracy of neural network forecasts. These factors include selection of input variables, preparing data, ANNs architecture. There is no consensus on these factors as they claimed. In different cases, various decisions have their own effectiveness. There is no formal systematic model building approach. The integration of neural networks with other technologies was reported. They also discussed the relative performance of ANNs compared with other forecasting methods, and then found mixed results.

They further submit that model uncertainty comes from three main sources: model structure, parameter estimation and data. The nonlinear nonparametric nature of ANNs may cause more uncertainties in model building. This learning and generalization dilemma or tradeoff has been extensive, and is still an active research topic in the field. To improve generalization performance of neural network models, they suggested that there may be the need to go beyond the model selection methods [21].

Neural network ensembles seem promising for improving predictions over the KTB approach because they do not solely rely on the performance of a single neural network model. It was further examined that three ensemble approaches are prominent. The first approach is to combine neural networks trained with different initial random weights but with the same data. The second approach is to combine different neural network architectures within an ensemble. The third approach is to combine networks trained with different sample data. Many other ensemble methods can be considered. For example, one potential method is based on bootstrapping samples randomly generated from the original whole training time series. While computationally expensive, ensemble models based on bootstrapping samples may provide further insights and evidence on the effectiveness of the ensemble method for out-of- sample forecasting. They recommended that research efforts should also be devoted to the methods that can further reduce the correlation effect in combining neural networks and to quantifying the impact that shifts in the data generation parameters have on the various approaches [21].

The exchange rates forecasted include Australian Dollar (AUD), Belgian/Luxembourg Franc (BEF/LUF), British Pound (GBP), Canadian Dollar (CAD), Danish Krone (DKK), Deutsche Mark (DEM), Dutch Guilder (NLG), French Franc (FRF), Greek Drachma (GRD), Irish Punt (IEP), Italian Lira (ITL), Japanese Yen (JPY), Korean won, Portuguese Escudo (PTE), Russian rouble, Spanish Peseta (ESP), Swiss Franc (CHF) and US Dollar (USD). Among them, USD, GBP, JPY, DEM are forecast most frequently [21].

They proposed that future research should attempt to formulate a hybrid neural network model for forecasting as follows: the model integrates ANNs with more complementary technologies to enhance its self-adaptation to different situations. More statistical analyses should be provided in determining some parameters like sample size and frequency, etc. We need to find out which kind of data segments best capture the underlying behavior of market changes. Appropriate sample frequency should be investigated to provide enough information on underlying relationship in exchange rates as well as to limit noise incorporation.

In addition, the continue by accepting that it is important to note that most studies use a single neural network model in modeling and predicting exchange rates. As data-dependent neural networks tend to be more unstable than traditional parametric models, performance of the keep-the-best (KTB) approach can vary dramatically with different models and data. Random variations resulting from data partitioning or subtle shifts in the parameters of the time series generating process can have a large effect on the learning and generalization capability of a single neural network model. These may be the reasons why neural networks perform differently for different exchange rate series and different time frequencies with different data partitions [21].

2.3.5 Modeling and Trading the EUR/USD Exchange Rate: Do Neural Network Models Perform Better?

It is expedient to ascertain whether Neural Network models perform well in predicting foreign exchange rates. Dunis and Williams [22], research examined and analyzed the use of Neural Network Regression (NNR) models in foreign exchange forecasting and trading models. The NNR models were benchmarked against traditional forecasting techniques to ascertain their potential added value as a forecasting and quantitative trading tool.

In addition to evaluating the various models using traditional forecasting accuracy measures, such as root mean squared errors, they were also assessed using financial criteria, such as risk-adjusted measures of return [22].

Having constructed a synthetic EUR/USD series for the period up to 4 January 1999, the models were developed using the same in-sample data, leaving the remainder for out-of-sample forecasting, October 1994 to May 2000, and May 2000 to July 2001, respectively. The out-of-sample period results were tested in terms of forecasting accuracy, and in terms of trading performance via a simulated trading strategy. Transaction costs were also taken into account.

They concluded that NNR models do have the ability to forecast EUR/USD returns for the period investigated, and add value as a forecasting and quantitative trading tool [22].

This substantiates the fact that neural network models are powerful tools for forecasting foreign exchange rates.

2.4 Forecasting Model used by Bank of Ghana

The Bank of Ghana (BoG) formally adopted IT in May 2007 after three years of informal IT management. It has been building the main institutional, analytical, and communications elements of this framework since 2002. With the enactment of the 2002 Bank of Ghana Act, the BoG had in place all of the key institutional components of modern central banking, especially independence and a statutory mission of price stability. In addition, central bank credit to the government each year is limited by law to 10 percent of total revenue collected that year, but in practice the government has not resorted to any central bank financing for the last several years. The target range for CPI inflation is set jointly by the government and the BoG as part of the budget. Staff describe the current regime as “inflation-targeting lite” because operational transparency has not developed sufficiently to classify it as a full-fledged IT regime [23].

When the BoG formally launched IT, it established a large measure of goal transparency, aiming for disinflation over three years to achieve stability around 5 percent, with a range of percent. It also announced a fairly straight-line path of intermediate inflation targets to get to 5 percent. In support of IT, the BoG has also developed a forecasting model and a detailed communication strategy. After each Monetary Policy Committee (MPC) meeting (every other month), it issues a press release and holds a press conference, chaired by the BoG Governor, at which it explains its decision. A detailed monetary policy report is then published.

In October 2007, inflation started to pick up again due both to demand shocks (from an expansionary fiscal policy and strong private sector credit growth) and to supply shocks (from higher international fuel and food prices). The BoG has noted that core CPI inflation – that excludes energy and utilities – has been lower than the headline but has also begun to rise. In response, the BoG has raised the policy rate by a cumulative 350 basis points since November 2007. These inflation developments have posed an early challenge for the IT regime. The current straight line disinflation path and communication strategy seem too rigid to respond well. As a results, the BoG credibility that was built up over the last four to five years may be at risk [23].

2.4.1 Standard Model

In the standard neo-Keynesian model in use at the Fund for several countries, the central bank sets an inflation target path dependent on current inflation and its long-run inflation objective and employs a Taylor-type rule to determine the policy (interest) rate, subject to the following behavioral equations:

- An output gap equation (actual minus potential output – a guage of excess demand – as a function of the interest rate the exchange rate and external
- An inflation rate equation (an expectations – augmented Phillips curve); and
- An exchange rate equation (a relation embodying uncovered interest parity, a variable risk premium, and long-run purchasing power parity).

In the standard model, the central bank's credibility is proxied by a parameter and is captured to some extent by the degree to which households form inflation expectations in a forward-looking rather than a backward-looking fashion. The standard model works reasonably well for countries that have already achieved low inflation rates, even though there is evidence that shows that a well managed IT framework will over time strengthen central bank credibility. However, it is less appropriate for Ghana because during disinflation periods credibility is likely to change over time, which is not endogenously captured in the standard model [23].

2.4.2 Model for Disinflation under Inflation Forecast Targeting.

The framework adds to the standard model three novel features relevant to a policy of inflation reduction:

- An endogenous credibility process. Starting from a situation in which agents initially expect inflation to remain high policymakers may build credibility over time by providing a sufficient tract record that anchors inflation to the target.
- A monetary policy loss function that recognizes costs of fluctuations in output and interest rates, as well as costs of deviations of inflation from target – in place of a conventional interest rate reaction function for the policy interest rate. The advantage of the loss function approach over reaction functions is that the responsiveness of interest rates will change automatically over time and will be more aggressive in responding to shocks when credibility is low.
- A non-linear Phillips curve. In practical terms, this means that the relationship of inflation and output gap depends on how big the output gap is. For very high output gap cases (high excess demand), small increases in output gap will translate into big increases in inflation. However, for reasonably low levels of excess demand, the relationship could be closer to a linear one. A non-linear Phillips curve serves to generate a number of

important predictions and policy implications that are missing from linear models that presume high levels of policy credibility. First, the model suggest that it can be easier to lose credibility than it is to regain once lost as it takes time and a period of significant slack in the economy to re-anchor inflation expectations. Second, this formulation strongly favors gradualism to prevent unnecessary cumulative output losses associated with disinflation.

The simulation results based on this model suggest that monetary policy should enable the BoG to reduce inflation while limiting output losses. The model is calibrated on the basis of a wide range of international experience and is frequently refined using a continuing iterative feedback process. Note that these results are simply indicative; they do not constitute staff recommendations but are merely one of several inputs into staff assessments. Model results should always serve as one of the several inputs into decision making by monetary policy-makers [23].

2.4.3 Simulation Results: Dynamic Responses to Shocks

We first study disinflation under imperfect and perfect credibility in the absence of shocks. Thereafter, we introduce supply and demand shocks and study both the policy reaction and the paths of all other economic variables [23].

- ***Baseline –Disinflation under Imperfect Credibility***

In the extended model, credibility is imperfect in the sense that people do not have full confidence that the central bank will achieve its announced objectives, and may not even believe that the bank will try to achieve them. In forming expectations of inflation, they give considerable weight to the recent history of inflation and to the risk that policymakers might have a covert high-inflation agenda. Monetary policy is assumed, however, to have some credibility: in the process of forming expectations; we set the initial weights at 0.4 on the announced low-inflation policy and at 0.6 on the alternative possibility of a high-inflation policy. Furthermore, the central bank can earn an increased stock of credibility – moving the low-inflation weight towards unity – only by delivering an actual drop in inflation toward the official objective [23].

Monetary policy in the model follows a loss-minimizing strategy to get to the assumed ultimate inflation target of 5 percent. We posit initial conditions similar to those prevailing in Ghana in the second quarter of 2008. The economy is experiencing excess demand pressures and has suffered an external price shock: inflation is high; growing fiscal deficits and easy monetary conditions are stimulating further inflation. In numerical terms, to start the model simulations we set the 2008:2 rate of inflation at 15.3 percent, the annual output gap (excess demand) at 0.5 percent; and the short-term rate of interest controlled by the central bank at 16 percent. The initial real interest rate is below 1 percent and hence much less than the assumed natural equilibrium rate of about 3 percent. We suppose that the central bank announces an ultimate target for the inflation rate of 5 percent in 2008:3 and immediately starts implementing the loss-minimizing policy to this end.

The charts in Figure 2.2 show the simulated disinflation path. Given the level of inflation expectations at the outset and lags in the expectations process, the central bank has to raise the policy rate substantially to achieve the desired increase in the real interest rate [23].

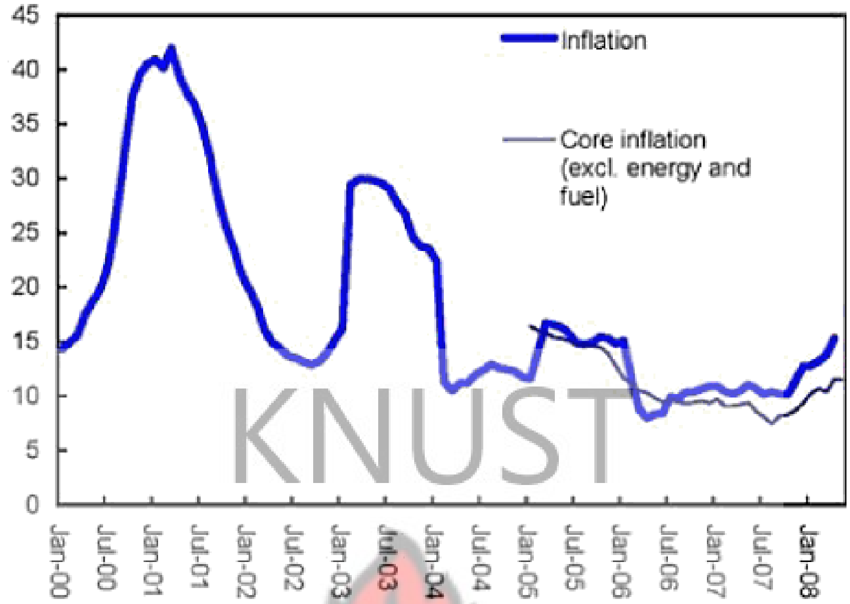


Figure 2.2: The simulated disinflation path

Optimal policy in the model – in the sense of achieving targeted disinflation with minimum loss in output – involved raising the interest rate to 19.6 percent in 2008:Q3, and to peak of 20 percent in 2008:Q4 [23].

2.5 Exchange Rate Converters

Performing conversions between the Ghanaian cedi and other currencies will delay operations when they are to be done manually. For easy conversion of the currencies that Ghanaian cedi trade with, there is the need to have an electronic tool that will calculate the conversion.

Ghana web provides an electronic currency converter. This tool provides the access to convert between currencies which include: US Dollar, Australian Dollar, British Pound, CFA Franc BCEAO.XOF, CFA Franc BEAC.XAF, Canadian Dollar, Danish Krone, Euro, Ghanaian cedi (both old and new), Japanese Yen, Libyan Dinar, New Zealand Dollar, Nigerian Naira, Norwegian Kroner, South African Rand, Swedish Krona, Swiss Franc, and Turkish Lira [24].

CoinMill.com has also provided an online currency converter sin the year 2003. This allows a user to convert the Ghanaian cedi to fifty-five different currencies which include all those available on Ghana web and more [25].

From 1997 OADA.com has significantly provided a currency converter which by the year 2003 made available the conversion between fifty-five currencies [26].

Among these three currency converters, the one provided by OADA.com seem to be more efficient and reliable than the others. This is because it makes it possible to convert between fifty five different currencies while the others allow only the conversion from Ghanaian cedis to other currencies.

2.6 Neural Network and Foreign Exchange

Nowadays, with the introduction of sophisticated information technology mechanisms, traders no longer need to rely on single indicators to provide information about the future trends of markets. They use a variety of indicators to obtain multiple signals. Neural networks are often trained by both technical and fundamental indicators to produce trading signals. Fundamental and technical analysis could be simulated in neural networks. For fundamental methods, retail sales, gold price, industrial production index, and foreign currency exchange rates etc. could be used as inputs. For technical methods, the delayed time series data together with the technical indicators such as moving averages, stochastics, relative strength index etc. could be used as input [30].

The purpose of this research is to establish a system that can predict the current exchange rate using neural network. It is upon this background that a system which will aid in forecasting the financial trend in order to help investors track the financial market trends.

2.7 Financial Market

The importance of financial markets for the development of a country's economy cannot be overemphasized. For this reason, many countries have embarked on a number of financial sector development programs since the mid of the 1980's in order to revamp their economies. For example Chile, 1980-1986, Bangledesh, 1980-1996 and India. India's Financial markets are now developed that most firms in the UK are moving there. For this reason, the question that needs asking is, "WHAT IS THE POSITION OF GHANA'S FINANCIAL MARKET, WHY IS IT AS IT IS AND WHERE IS IT GOING (THE FUTURE)? [31].

In financial management, as this research purports to consider, involve a system of collection and presentation of relevant economic information relating to an enterprise for planning, controlling and decision making. The four main financial securities which include shares, bonds, Treasury Bills and Stock Exchange are the major determinants in financial market.

CHAPTER THREE: ANALYSIS AND DESIGN

3.1 Introduction

Upon the review of the various work done by others on the application of neural network as well as papers written on neural networks in relation to financial systems, this chapter takes a critical look at the methodology of research which is based on feedforward neural network model. Furthermore, the analysis of the proposed system, thus, a system to implement neural network in financial market is considered. The analysis therefore, includes the functional, input as well as processing requirements.

The design of the system is established under this chapter. This includes the design of the algorithm of the proposed system which is derived and improved model from feedforward neural network with one hidden layer used by Faraway and Chartfield [17].

3.2. Analysis of Proposed System

Realizing that the various systems being reviewed in the previous chapter are not fully capable of producing consistent and accurate result in forecasting and predicting financial market trends, proceedings could be made to analyze the selected model. This model, though not perfect, could be adopted and modified to output consistent and accurate result in predicting financial market trends, with specific reference to predicting the future values of exchange rate.

3.2.1 Requirements Analysis

The system is required to accept the previous values of exchange rate as input, simulate the data obtained and predict the possible exchange rates in the future. Financial institutions will then be able to trade in the world market by making feasible projections. Investors will have an idea of how the status of their capital as well as profit margin since the future financial market trends can be obtained from the predictions made by the system.

3.2.2 Functional Requirements

There are important functions that the system must deliver in order to meet the user requirements. These functions are termed functional requirements. The functional requirements under this system include:

- Ability to accept previous data on exchange rates in (the constant input terms) in the financial market.
- The Bank of Ghana to keep the previous data on exchange rates in the financial market.
- Ability to obtain a numerical value for each neuron which is calculated in two stages based on the adopted model.
- Ability to implement neural network model for time-series data to obtain result of accurate prediction by combining general traditional modeling skills linked with knowledge of time-series analysis and the particular problems involved in fitting neural models.

3.2.3 Input Requirements

The basic fundamental input of this system is the previous values of the financial securities in the financial market. For the purposes of the limitation of this research to exchange rates, the input is the previous values of exchange rates in financial market. All other inputs which are not specific are considered as derived input which may be fed into the system when the necessity arises.

3.2.4 Processing Requirements

The major processing requirement of this system is the comparison of the previous values of exchange rates. This is to ascertain whether the cedi appreciated or depreciated against the foreign currency in the financial market. Upon the values obtained, the system will forecast and predict future trends using artificial neural network model. The predictions will be made to give a projection on how the foreign exchange rate will stand considering the previous values.

3.3 Design of Proposed System

The model under consideration, feedforward neural network with one hidden layer of three neurons is designed and implemented with the system requirements. This is show how the execution of the data, thus the prediction of the exchange rates of the various currencies under consideration.

3.3.1 Processing Modeling

The required data for processing in this research is the previous values of financial market. Specifically, banks indicative opening rates of the various popular currencies of which are obtained from Bank of Ghana on weekly basis are the fundamental data. Following are tables depicting the banks indicative rates of every weekend in the month of July 2010.

3.3 The Algorithm

At this stage of the research, the attention to one (popular) form of (artificial) neural network called feedforward neural network with one hidden layer is considered in deriving the model for the forecasting. In financial forecasting, we wish to predict future observations of exchange rates using some function of past observations. A supervised learning paradigm is employed, thus, we wish to infer the mapping implied by the data; the exchange rate function is related to mismatch between the mapping and the data and it implicitly contains prior knowledge about the problem domain.

Figure 3.1 illustrates an architecture as applied to the forecasting of the foreign exchange rate using three neurons with softmax activation functions.

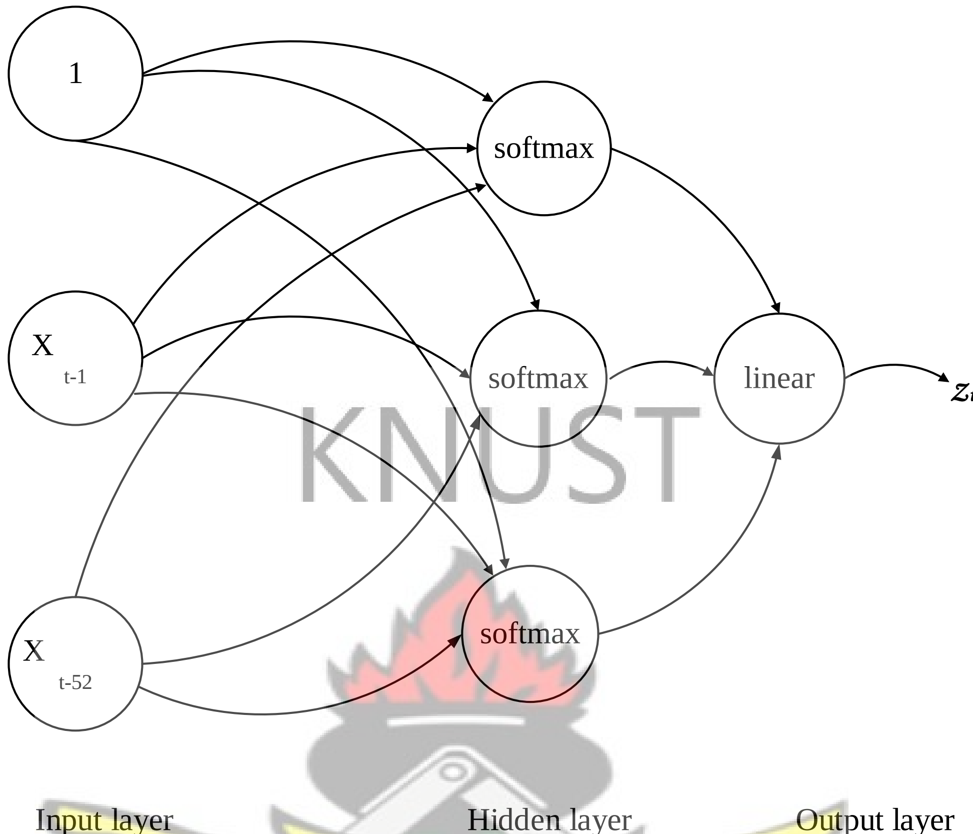


Figure 3.1: The architecture of neural network for forecasting with one hidden layer of 3 neurons.

The value at time *t* is to be forecasted using the values at lags one and fifty-two. The latter are regarded as *input* while the forecast is the *output*. The illustrated structure includes one hidden layer of three *neurons* (often referred to as *nodes* or *processing units* or just *units*). In addition, there is also a constant input term which for convenience may be taken as unity. Each input is connected to all the (hidden) neurons, and all neurons are connected to the output. The "strength" of each connection is measured by a rate. A numerical value is calculated for each neuron in two stages. First, a linear function of the inputs is found, say $\sum_{i=1}^{3} r_{in} y_i$ where r_{in} denotes the rate of the connection between input y_i and the *n*th neuron. The values of the inputs in the example under consideration are y_1 = unity, $y_2 = x_{t-1}$ and $y_3 = x_{t-52}$. The linear sum, say s_n, is then transformed by applying a function called an *activation function*, which is typically non-linear. In this case we use the *softmax activation function*, $\lambda_n = \frac{e^{s_n}}{\sum_{n=1}^{3} e^{s_n}}$ which gives values in the range (0, 1). However, this leads to values $\boldsymbol{\lambda}_1$, $\boldsymbol{\lambda}_2$ and $\boldsymbol{\lambda}_3$ for the three neurons. By assigning a softmax activation function on the output layer of the neural network (or a softmax component in a component-based neural network) for categorical target variables, the output can be interpreted as posterior probabilities [33]. This is very useful in classifications as it gives a certainty measure on classifications.

The introduction of a constant input unit connected to every neuron in the hidden layer and also to the output avoids the necessity of separately introducing what computer scientists call a *bias*, and statisticians would call an intercept term, for each unit. Essentially the biases just become part of the set of rates (the parameters).

For a neural network model with one hidden layer, the general prediction equation for computing a forecast of $\boldsymbol{z_t}$ (the output) using selected past observations, $\boldsymbol{x_{t-n1}, \ldots, x_{t-nk}}$ as the inputs, may be written (rather messily) in the form:

$$\boldsymbol{z_t} = \delta_0[r_{co} \textstyle\sum_n r_{no} \lambda_n (r_{cn} + \sum_n r_{in}\, x_{t-nk})] \qquad 3.1$$

where $\{r_{cn}\}$ denote the rates for the connections between the constant input and the hidden neurons and r_{co} denotes the rate of the direct connection between the constant input and the output. The rates $\{r_{in}\}$ and $\{r_{no}\}$ denote the rate for the other connections between the inputs and the hidden neurons and between the neurons and the output respectively. One minor point to note is that the labels on the hidden neurons can be permuted without changing the model. The two functions $\boldsymbol{\lambda}_n$ and δ_o indicate the activation functions used at the hidden layer and at the output respectively. Throughout this model,

λ_n is taken to be the softmax function whereas δ_o is taken to be the identity function in order to ensure, as noted earlier, that the forecasts are not restricted to the range (0, 1). The use of the notation $NN(n_i, \ldots, n_k,; h)$ to signify the neural network with lags $n_i, \ldots, n_k$, and h neurons (or units) in the one hidden layer. Thus Fig. 3.1 represents a $NN(1, 52; 3)$ model.

The rates to be used in the neural network are estimated from the data by minimizing the sum of squares of the within-sample one-step-ahead forecast errors, $r = \sum_t (x_{t-52} - x_{t-1})^2$ over the first part of the time series, called the *training set* in neural network jargon. The minimization is no easy task as the objective function often has several local minima and the number of rates may be large. The training algorithm for selecting the rates may take several iterations to converge, but may still converge to a local minimum. The starting values chosen for the rates can be crucial and it is advisable to try several different set of starting values to see if consistent results are obtained. It is obvious that other packages perform the numerical fitting in different ways. For example, *simulated annealing* is a technique that can be employed to try to avoid local minima but this requires the analyst to set numerical parameters, and even then there is no guarantee that convergence to a global minimum will occur.

The *test set*, being the last part of the time series, is kept in reverse so that genuine out-of-sample forecast can be made and compared with the actual observations.

As established, equation (1) effectively gives a one-step-ahead forecast as it uses the actual observed values of all lagged variables as inputs. If multi-step-ahead forecasts are required, then it is possible to proceed in one of two ways. Firstly, one could construct a new architecture with several outputs, giving z_t, z_{t+1}, z_{t+2}, …., where each output would have separate rates for each connection to the neurons. Secondly, one could ‘feed back’ the one-step-ahead forecast to replace the lag-one value as one of the input variables and the same architecture could then be used to construct the two-step-ahead forecast, and so on. The latter iterative approach is adopted, as did Hill *et al*., because of its numerical simplicity and because it requires fewer rates to be estimated.

As we continue to establish, even so, the number of parameters in a neural network model is typically much larger than in traditional time-series models, and for a single-layer neural network model is given by $p = (n_i +2)\ n_h + 1$ where n_i denotes the number of input variables (excluding constant) and n_h denotes the number of hidden neurons. For example the architecture in Fig 3.1 (where n_i and the n_h are two and three respectively) contains 13 connections and hence has 13 parameters (rates). Because of this large number, there is a real danger that the algorithm may “overtrain’ the data and produce a spuriously good fit which does not lead to better forecasts. Some research has focused on the need to penalize the fitting of extra parameters rather than just optimize goodness-of-fit, and the use of something like Akaike’s information criterion (AIC) is needed to prevent the fitting of spurious parameters.

“Neural network modeling is non-parametric in character and it has been proposed that the whole process can be completely automated on a computer so that people with little knowledge of either forecasting or neural networks can prepare reasonable forecasts in a short space of time”[18]. The result of accurate prediction can be obtained when a good neural network model for time-series data must be selected by combining general traditional modeling skills linked with knowledge of time-series analysis and the particular problems involved in fitting neural models.

3.4 Pseudocode

The pseudocode for this research as derived from the algorithm is outlines as follows:

BEGIN

STEP 1: Define the currency to be forecast

2: Define constant input variables $y_{1 = 1}$

3: Define input variable x_{t-1}, ……., x_{t-52}

4: Compute rate for connection between constant input and the hidden neuron,

$$r_{cn} = (\mathrm{x}_{t-1} - 1)^2 \tag{3.2}$$

i: subtract constant input y_1 from first initial input

ii: multiply the result by itself

5: Compute rate for direct connection between constant input and the output,

$$r_{co} = (\mathrm{x}_{t-52} - 1)^2 \tag{3.3}$$

i: subtract constant input y_1 from last observable input

ii: multiply the result by itself

6: Compute the rates for the other connections between input and hidden neuron,

$$r_{in} = \sum_t (\bar{\mathrm{x}}_t - \mathrm{x}_{t-i})^2 \tag{3.4}$$

i: compute mean of all observable input

while(t > 0)

sum all observable input values (x_t)

divide the sum by the total number of observable input (t)

ii: while(t > 0)

subtract each observable input from mean

multiply the result by itself

sum all the result at every iteration

7: Compute the rates for the other connections between the hidden neuron and the output,

$$r_{no} = (\bar{x}_t - x_{t-52})^2 \qquad 3.5$$

i: subtract last observable input from the mean

ii: multiply the result by itself

8: Compute input function,

$$s_n = \sum_{i=1}^{t} r_{in} x_{t-i} \qquad 3.6$$

while (i < t), where i controls the input

multiply r_{in} by all observable input

sum the all the results of each products

9: Transform input function by applying softmax activation function,

$$\lambda_n = \frac{e^{s_n}}{\sum_{n=1}^{3} e^{s_n}} \qquad 3.7$$

i: define the constant **e** = 2.71828

ii: iterate **e** by s_n times

iii: while(n < 3)

add the iterated value to itself

iv: divide result in (ii) by the result in (iii)

10: compute the forecast value

$$\boldsymbol{z}_t = \delta_0[r_{co} \sum_n r_{no} \lambda_n (r_{cn} + \sum_n r_{in} x_{t-nk})] \qquad 3.8$$

i: multiply r_{no} by λ_n

ii: while (n > 0), where n is number of neurons

add the result in (i) to itself

iii: multiply result in (ii) by r_{co}

iv: multiply r_{in} by the observable input values

v: sum the products in the (iv)

vi: add r_{cn} to the result in (v)

vii: define the identity function δ_0, here δ_0 is 1

viii: multiply result in (vi) by δ_0 and keep result in $\boldsymbol{z_t}$

11: Display the forecast value, z_t

END

This pseudocode will be used for the prediction of exchange rate of all currencies.

3.5 The System Flowchart

A diagrammatical representation of the pseudocode above is presented in the system flowchart which depicts the flow of operations in the "feedforward" neural network model.

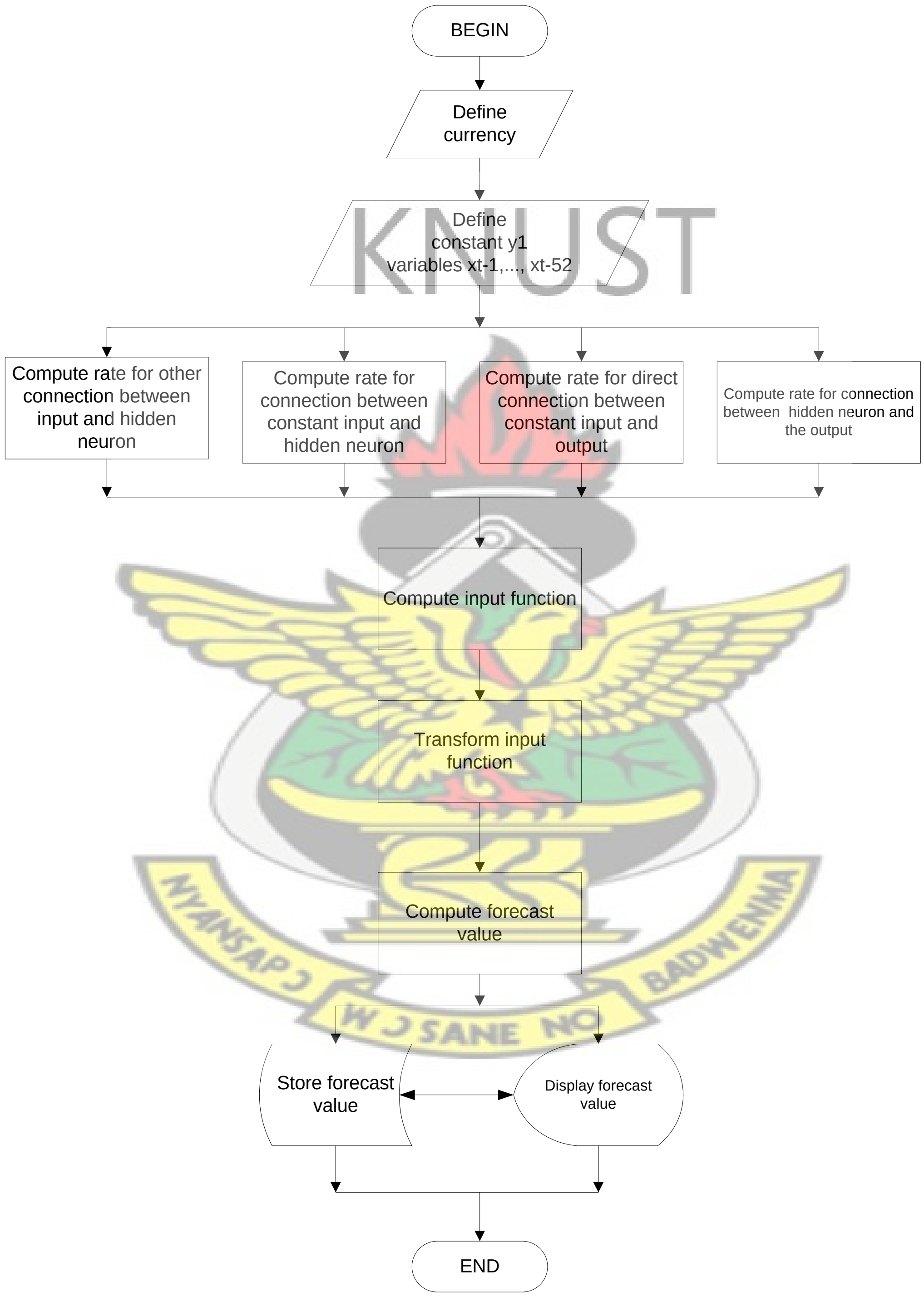


Figure 3.2: System Flowchart

CHAPTER FOUR: IMPLEMENTATION AND TESTING

4.1 Introduction

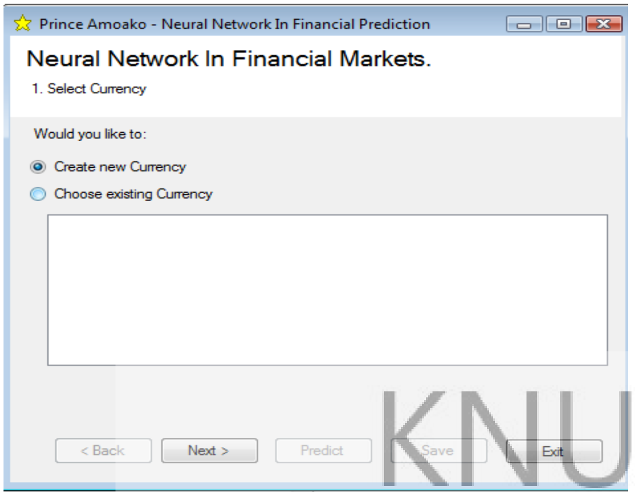
Forecasting exchange rate has been the focus of this research although a broader view of forecasting financial market trend taking into consideration the various financial securities, such as treasury bills, shares and bonds. All these securities are directly affected by the exchange rate.

Implementing the feedforward neural network in predicting the exchange rate using the previous weekly observations is the center of attention of the chapter. This implementation is achieved through the coding of the pseudocode algorithm deduced from the analysis in the previous chapter. The programming language being used is C# (C sharp). C# is used because, it is very easy to implement and as well can be implemented in distributed systems or web based applications.

4.2 System implementation

The system, after login allows the user to begin by creating the currency of which he or she desires to predict its exchange rate in the local currency, thus cedis. As part of the limitations, the system will consider the creation of three foreign currencies; namely, United States Dollars, United Kingdom Pound Sterling and the European Union Euros. The interface for creating a currency is shown below:

As can be observed Figure 4.1 and Figure 4.2, the user can create a new currency and if there is an existing currency then the user can select from it and proceed with predicting the exchange rate.



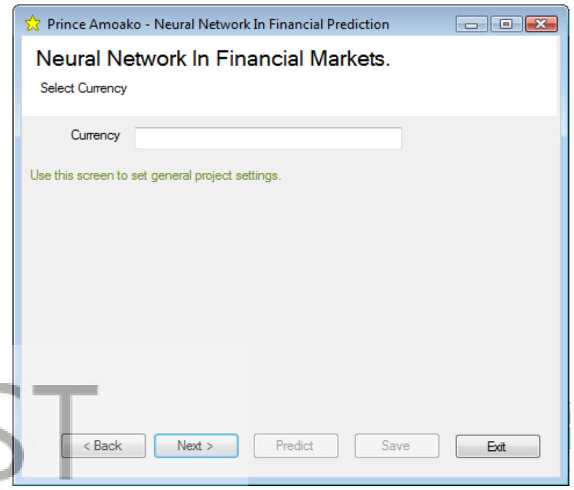


Figure 4.1: Select currency screen **Figure 4.2: Create currency screen**

But at the initial state, after creating the currency the user will be required to read in the fifty-two (52) input data. This is the previous weekly exchange rates for the past year. The interface for the data input is displayed in Figure 4.3;

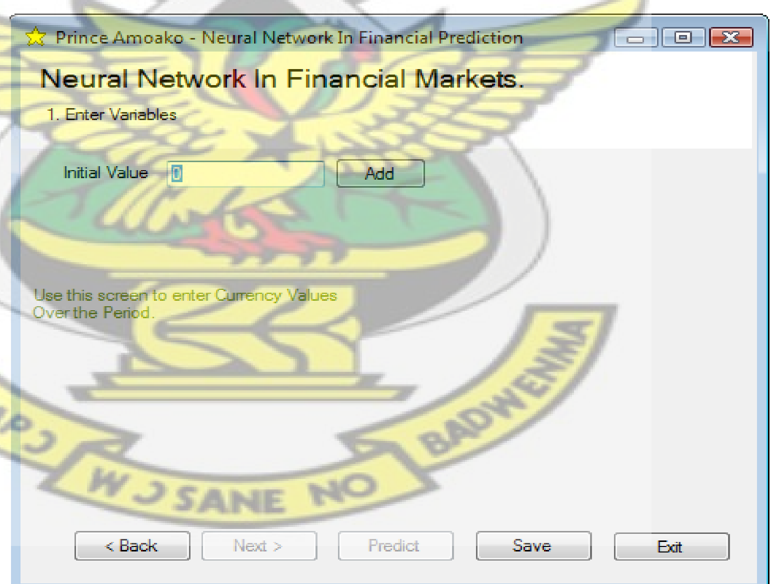


Figure 4.3: Data input screen

After each input the Add button or the return key is pressed to allow for the next input. The user has access to return to the previous window when realized there is a mistake with the operation or entry and rectify it by using the back button. The next button is used to move to the next stage of the operation.

Upon completing the entries, the system allows the user to perform two operations, either to save the input data or to predict the exchange rate for the future. The predict button will be activated when all the 52 input data has been fed into the system. The system also allows the user to save the input data at every point of entry; thus, the entries can be suspended and continue later.

Now Figure 4.4 depicts the processes and the final prediction of the exchange rate.

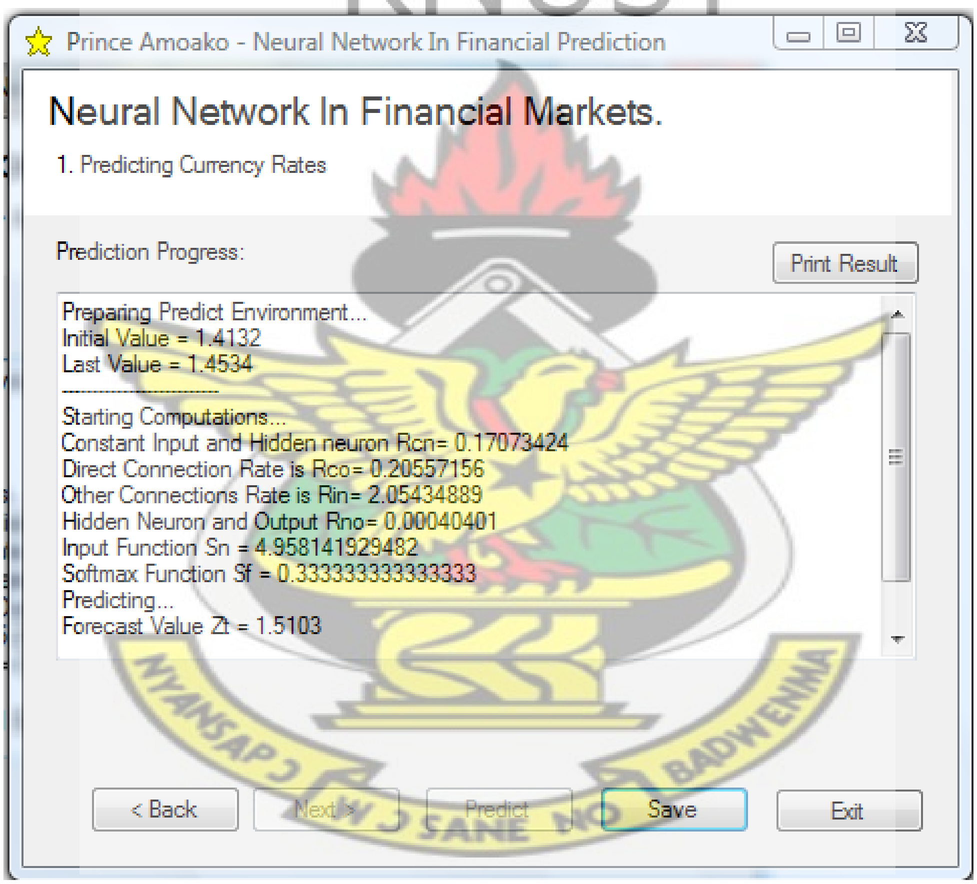


Figure 4.4: Prediction screen

The first and fifty-second input values are displayed, and then begin with the computations. The result of the rate between the constant input and the hidden layer is displayed and then the rate of direct connection between the input and the output. The value of the rate of other connections between the input and the hidden neuron and also between the hidden neuron and the output are displayed. The input function as well as the softmax activation function are displayed and finally the forecast value is shown.

We can save the currency that has been predicted by clicking on the save button. A dialog box displays to show that the currency is saved and that it can be selected and use for future predictions. Figure 4.5 depicts such function of the system.

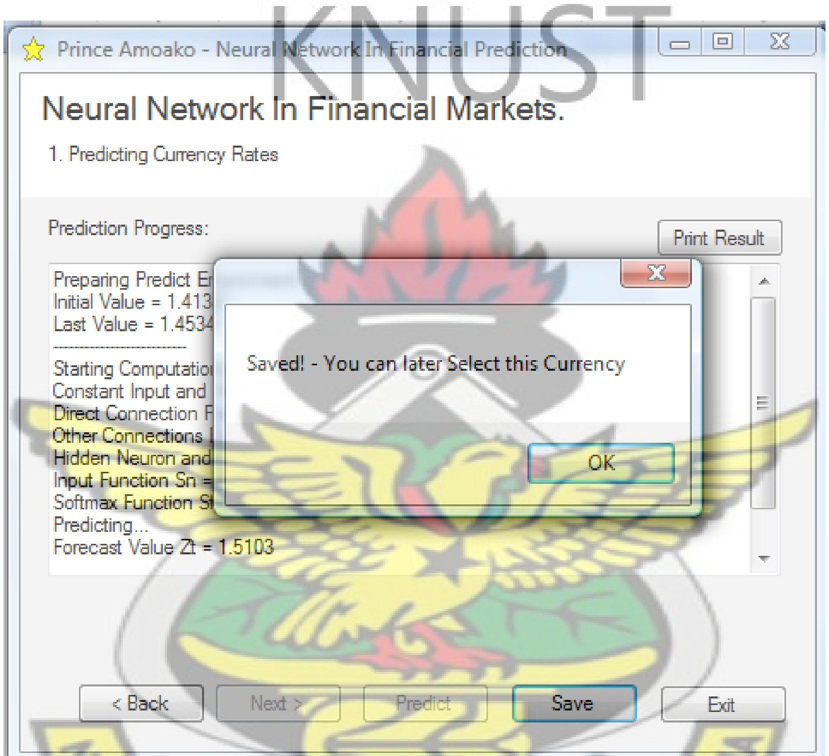


Figure 4.5: Saving a currency

In view of this when the system executes again it provides that functionality by displaying the currencies already created in the text field as shown in Figure 4.6.

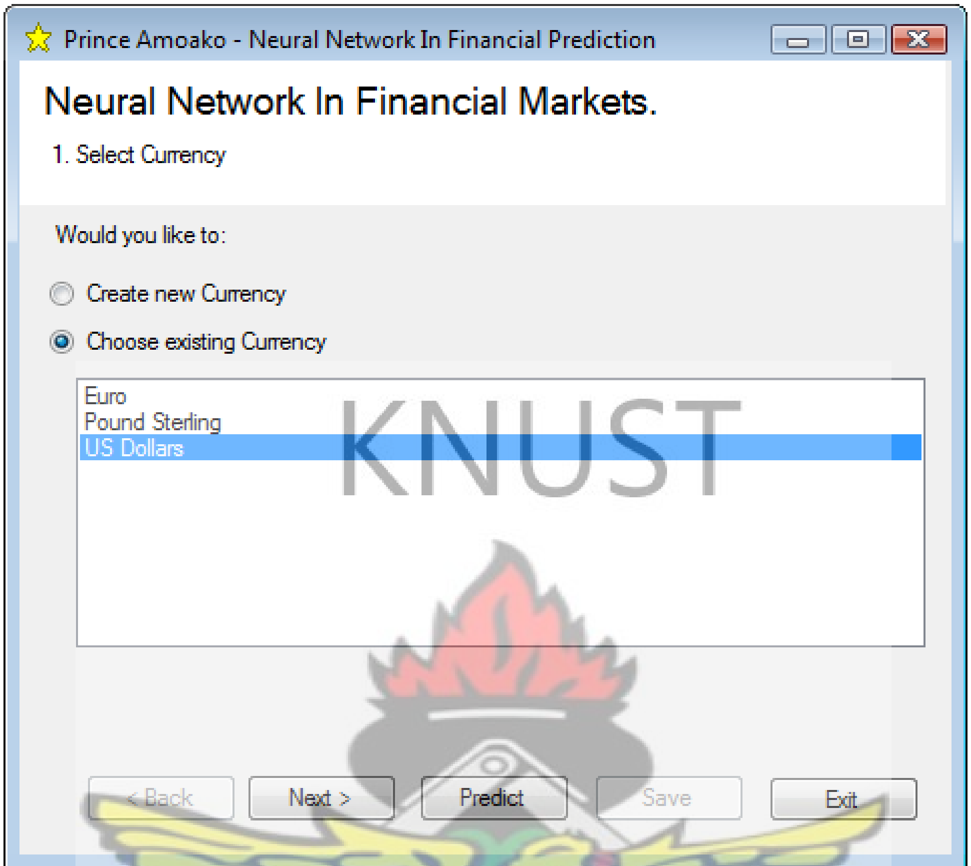


Figure 4.6: Existing currencies

We can therefore click on predict to display the existing prediction or we can also alter the input to obtain new prediction by clicking on next. Again the system allows you to create a new currency and begin with the input and finally predict for the new currency.

The system allows for the creation of more currencies and then predicts their forecast values. This system is generic to all currencies that Bank of Ghana relates to with respect to exchange rates. It can therefore be used to forecast and predict the exchange rates although in its system testing only three currencies, Banks-Indicative Opening U.S. Dollars Rates – Selling, Banks-Indicative Opening Pound Sterling Rates and Banks-Indicative Opening Euro Rates – Selling were considered.

4.3 Testing

A simulation is run with the three currencies, Banks-Indicative Opening U.S. Dollars Rates – Selling, Banks-Indicative Opening Pound Sterling Rates - Selling and Banks-Indicative Opening Euro Rates – Selling. The test data was exchange rates for the three currencies for the year 2010 obtained from Bank of Ghana. The opening rates of each week given fifty-two (52) weeks and hence 52 input. Table 4.1 through Table 4.4 show the data obtained from Bank of Ghana on exchange rates. The four weeks in the month of July in the year 2010 are captured in these tables depicting the available currencies with their rate against the Ghanaian cedi. The four tables are also presented here as sample to bring out the differences in the exchange rate for each week of which the fifty-two input for the year 2010 are obtained from.

Table 4.1 : Monday 05th July 2010

Banks-Indicative Opening Rates

Currency	**Pairs Code**	**Buying**	**Selling**
U.S. Dollar	USDGHS	1.417	1.4364
Pound Sterling	GBPGHS	2.1502	2.18
Swiss Franc	CHFGHS	1.332	1.3495
Australian Dollar	AUDGHS	1.194	1.2117
Canadian Dollar	CADGHS	1.3347	1.3521
Danish Kroner	DKKGHS	0.2385	0.2416
Japanese Yen	JPYGHS	0.0161	0.0164
New Zealand Dollar	NZDGHS	0.9785	0.993
Norwegian Kroner	NOKGHS	0.2201	0.2229
Swedish Kroner	SEKGHS	0.1852	0.1876
S/African Rand	ZARGHS	0.1838	0.1851
Euro	EURGHS	1.7771	1.8011
BCEAO	GHSXOF	364.2	369.11
Dalasi	GHSGMD	20.3	20.57
Ouguiya	GHSMRO	190.87	193.49
Naira	GHSNGN	113.75	193.49
Leone	GHSSLL	2,906.34	115.31
WAUA	WAUAGHS	0.4973	2,946.13

Table 4.2: Monday 12th July 2010

Banks-Indicative Opening Rates

Currency	Pairs Code	Buying	Selling
U.S. Dollar	USDGHS	1.4197	1.4401
Pound Sterling	GBPGHS	2.126	2.157
Swiss Franc	CHFGHS	1.3331	1.3517
Australian Dollar	AUDGHS	1.2369	1.2558
Canadian Dollar	CADGHS	1.3759	1.3951
Danish Kroner	DKKGHS	0.2397	0.243
Japanese Yen	JPYGHS	0.016	0.0162
New Zealand Dollar	NZDGHS	1.0056	1.0211
Norwegian Kroner	NOKGHS	0.2222	0.2254
Swedish Kroner	SEKGHS	0.1888	0.1914
S/African Rand	ZARGHS	0.1878	0.1903
Euro	EURGHS	1.7861	1.8116
BCEAO	GHSXOF	362.09	367.26
Dalasi	GHSGMD	20.28	20.57
Ouguiya	GHSMRO	190.74	193.49
Naira	GHSNGN	113.67	115.31
Leone	GHSSLL	2,904.29	2,946.13
WAUA	WAUAGHS	0.4961	

Table 4.3 : Monday 19th July 2010

Banks-Indicative Opening Rates

Currency	Pairs Code	Buying	Selling
U.S. Dollar	USDGHS	1.4217	1.4431
Pound Sterling	GBPGHS	2.1795	2.2127
Swiss Franc	CHFGHS	1.359	1.3791
Australian Dollar	AUDGHS	1.2382	1.2577
Canadian Dollar	CADGHS	1.3512	1.3709
Danish Kroner	DKKGHS	0.2475	0.2512
Japanese Yen	JPYGHS	0.0164	0.0166
New Zealand Dollar	NZDGHS	1.0093	1.0256
Norwegian Kroner	NOKGHS	0.2263	0.2294
Swedish Kroner	SEKGHS	0.1937	0.1961
S/African Rand	ZARGHS	0.1866	0.1893
Euro	EURGHS	1.8451	1.8725
BCEAO	GHSXOF	350.32	355.51
Dalasi	GHSGMD	20.27	20.57
Ouguiya	GHSMRO	190.62	193.49
Naira	GHSNGN	113.6	115.31
Leone	GHSSLL	2,902.44	2,946.13
WAUA	WAUAGHS	0.4953	

Table 4.4 : Monday 26th July 2010

Banks-Indicative Opening Rates

Currency	Pairs Code	Buying	Selling
U.S. Dollar	USDGHS	1.4258	1.4478
Pound Sterling	GBPGHS	2.206	2.2405
Swiss Franc	CHFGHS	1.3541	1.3747
Australian Dollar	AUDGHS	1.2786	1.2995
Canadian Dollar	CADGHS	1.3774	1.3981
Danish Kroner	DKKGHS	0.2474	0.2511
Japanese Yen	JPYGHS	0.0164	0.0166
New Zealand Dollar	NZDGHS	1.041	1.058
Norwegian Kroner	NOKGHS	0.231	0.2338
Swedish Kroner	SEKGHS	0.195	0.1976
S/African Rand	ZARGHS	0.1928	0.1957
Euro	EURGHS	1.8437	1.8718
BCEAO	GHSXOF	350.45	355.78
Dalasi	GHSGMD	20.26	20.57
Ouguiya	GHSMRO	190.55	193.49
Naira	GHSNGN	113.56	115.31
Leone	GHSSLL	2,901.37	2,946.13
WAUA	WAUAGHS	0.4938	

4.4 Results and Discussion

The results of the simulation of each currency are then presented statistically using a Sample Paired T Test to infer a comparison between the actual and predicted data.

4.4.1 U.S. Dollar Rate Predictions

Upon running the system designed to perform the prediction of exchange rate by implementing artificial neural network model based on previous Banks-Indicative Opening U.S. Dollar Rates – Selling (thus, year 2010) weekly data on exchange rate a statistical evaluation is made.

The actual and the predicted values of the Banks-Indicative Opening U.S. Dollar Rates – Selling for the first quarter of year 2011 with their corresponding differences are shown in table 4.4.1.

Table 4.4.1: Actual and Predicted, Banks-Indicative Opening U.S. Dollar Rates – Selling

Date	Actual Rate	Predicted Rate	Difference
Friday 7th January 2011	1.4708	1.4810	0.0102
Friday 14th January 2011	1.4753	1.4875	0.0122
Friday 21th January 2011	1.4786	1.4912	0.0126
Friday 28th January 2011	1.4959	1.5103	0.0144
Friday 4th February 2011	1.5362	1.5563	0.0201
Friday 11th February 2011	1.5339	1.5649	0.0310
Friday 18th February 2011	1.5281	1.5571	0.0290
Friday 25th February 2011	1.5290	1.5465	0.0175
Friday 4th March 2011	1.5293	1.5497	0.0204
Friday 11th March 2011	1.5299	1.5598	0.0299
Friday 18th March 2011	1.5314	1.5616	0.0302
Friday 25th March 2011	1.5352	1.5588	0.0236
TOTALS	**18.1736**	**18.4425**	**0.2689**

On the statistical presentation a Paired Sample T-Test is used.

From Table 4.4.2 the predicted mean rate (1.536875) is higher than the actual mean rate (1.514542) indicating a difference between the predicted values and the actual values.

Table 4.4.2: Paired Samples Statistics - U.S. Dollar

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	Actual	1.514542	12	.0261449	.0075474
	Predicted	1.536875	12	.0318656	.0091988

From Table 4.4.3 we realized that there is a strong positive correlation between the actual Banks-Indicative Opening U.S. Dollar Rates – Selling and the predicted Banks-Indicative Opening U.S. Dollar Rates – Selling. This is observed from the correlation value .981.

Table 4.4.3: Paired Samples Correlations - U.S. Dollar

		N	Correlation	Sig.
Pair 1	Actual & Predicted	12	.981	.001

The Paired Samples T Test used compares the means of actual and predicted Banks-Indicative Opening U.S. Dollar Rates – Selling. It computes the difference between the two variables for each case, and tests to see if the average difference is significantly different from zero.

From table 4.4.4 we realize the descriptive statistics for the difference between the actual and predicted Banks-Indicative Opening U.S. Dollar Rates – Selling.

Table 4.4.4: Paired Samples Test - U.S. Dollar

	Paired Differences					t	df	Sig. (2-tailed)
	Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
				Lower	Upper			
Pair 1 Actual - Predicted	-.0223333	.0079954	.0023081	-.0274134	-.0172533	-9.676	11	.000

The t value is -9.676 with 11 degrees of freedom (df) presenting a significance value of .000 for the 2-tailed test. Since the significance value is less than .05, there is no significant difference between the actual and predicted Banks-Indicative Opening U.S. Dollar Rates – Selling. Hence, we can therefore conclude that at 95% confidence interval of the difference the prediction is very close to the actual.

Figure 4.8 shows the graphical presentation of the actual and predicted Banks-Indicative Opening U.S. Dollar Rates – Selling for the first quarter of the year 2011. The two graphs confirm the closeness of the predicted values to the actual values.

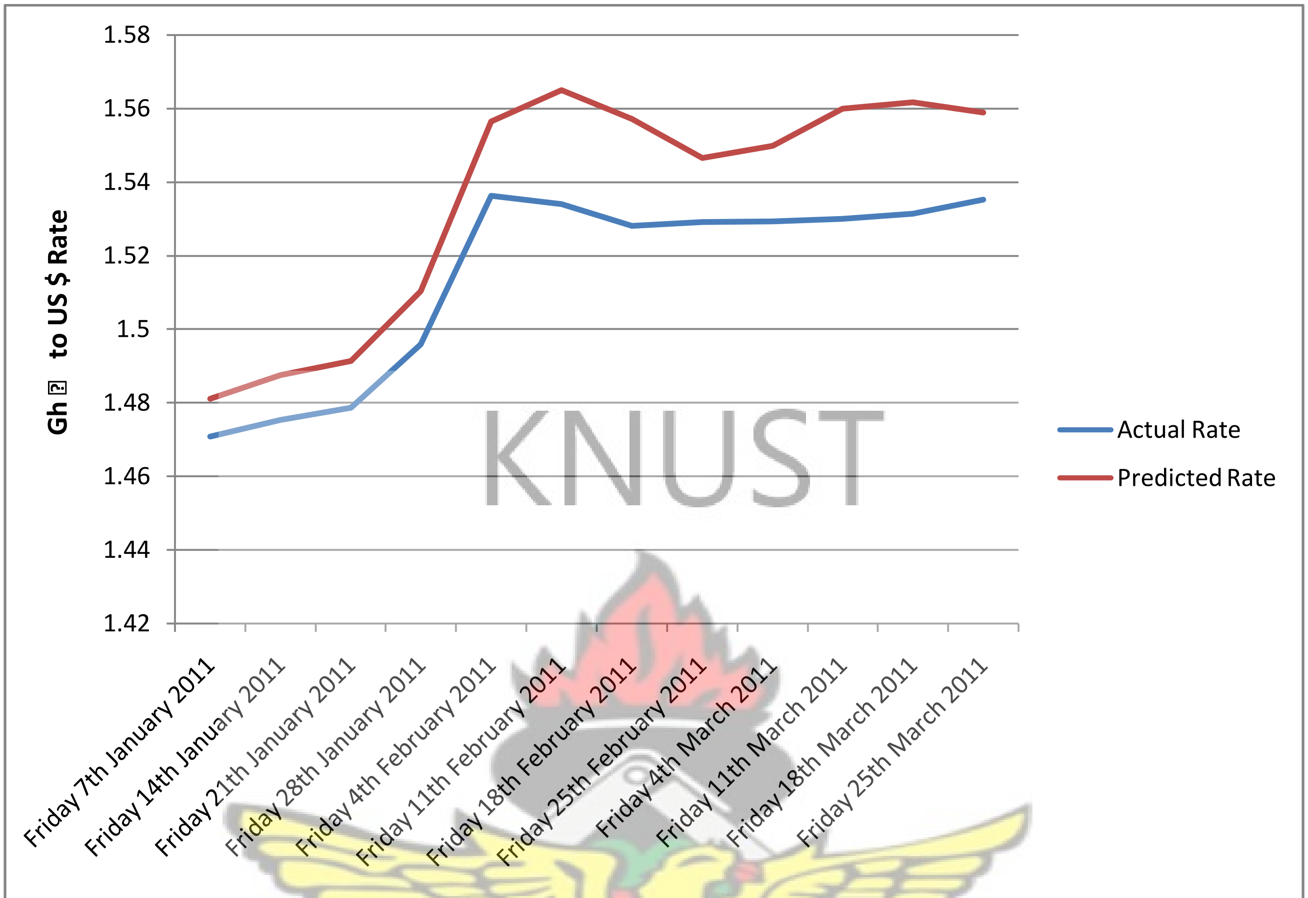


Figure 4.8: **Line graph of Actual and Predicted rates - U.S. Dollar**

4.4.2 Pound Sterling Rate Predictions

Again, system is tested on previous Banks-Indicative Opening Pound Sterling Rates – Selling and the outcome is presented statistically to evaluate its performance.

The actual and the predicted values of the Banks-Indicative Opening Pound Sterling Rates – Selling for the first quarter of year 2011 with their corresponding differences are revealed in Table 4.4.5.

Table 4.4.5: Actual and Predicted Banks-Indicative Opening Pound Sterling Rates – Selling

Date	Actual Rate	Predicted Rate	Difference
Friday 7th January 2011	2.2722	2.3934	0.1212
Friday 14th January 2011	2.3371	2.5602	0.2231
Friday 21th January 2011	2.3551	2.5711	0.2160
Friday 28th January 2011	2.3736	2.5828	0.2092
Friday 4th February 2011	2.484	2.6251	0.1411
Friday 11th February 2011	2.4642	2.6670	0.2028
Friday 18th February 2011	2.4747	2.6535	0.1788
Friday 25th February 2011	2.4689	2.6713	0.2024
Friday 4th March 2011	2.4894	2.6321	0.1427
Friday 11th March 2011	2.4546	2.6312	0.1766
Friday 18th March 2011	2.4721	2.6801	0.2080
Friday 25th March 2011	2.4734	2.6911	0.2177

From Table 4.4.6 the predicted mean rate (2.613242) is higher than the actual mean rate (2.426608) indicating a difference between the predicted values and the actual values.

Table 4.4.6: Paired Samples Statistics – Pound Sterling

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	Actual	2.426608	12	.0723443	.0208840
	Predicted	2.613242	12	.0815077	.0235292

From Table 4.4.7 we can infer that there is a strong positive correlation between the actual Banks-Indicative Opening Pound Sterling Rates – Selling and the predicted Banks-Indicative Opening Pound Sterling – Selling. This is pragmatic from the correlation value .906.

Table 4.4.7: Paired Samples Correlations – Pound Sterling

		N	Correlation	Sig.
Pair 1	Actual & Predicted	12	.906	.000

The Paired Samples T Test used compares the means of actual and predicted Banks-Indicative Opening Pound Sterling – Selling. It computes the difference between the two variables for each case, and tests to see if the average difference is significantly different from zero.

From Table 4.4.8 we realize the descriptive statistics for the difference between the actual and predicted Banks-Indicative Opening Pound Sterling Rates – Selling.

Table 4.4.8: Paired Samples Test – Pound Sterling

	Paired Differences					t	df	Sig. (2-tailed)
	Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference Lower	Upper			
Pair 1 Actual - Predicted	-.1866333	.0344833	.0099545	-.2085430	-.1647237	-18.749	11	.000

The t value is -18.749 with 11 degrees of freedom (df) presenting a significance value of .000 for the 2-tailed test. In view of the fact that the significance value is less than .05, there is no significant difference between the actual and predicted Banks-Indicative Opening Pound Sterling Rates – Selling. In conclusion, we can therefore say that at 95% confidence interval of the difference the prediction is very close to the actual.

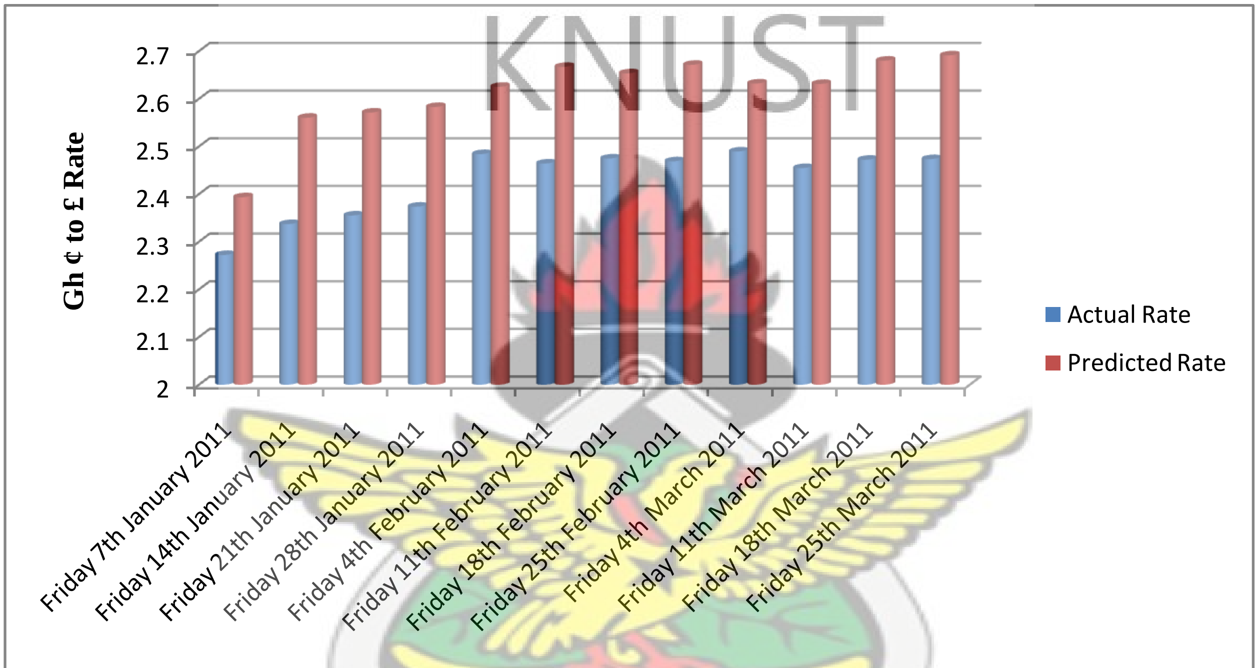


Figure 4.9: Bar graph of Actual and Predicted rates – Pound Sterling

Figure 4.4.9 shows the graphical presentation of the actual and predicted Banks-Indicative Opening Pound Sterling Rates – Selling for the first quarter of the year 2011. The two graphs substantiate the closeness of the predicted values to the actual values.

4.4.3 Euro Rate Predictions

Again, system is tested on previous Banks-Indicative Opening Euro Rates – Selling and the outcome is presented statistically to evaluate its performance.

Table 4.4.9 depicts the actual and the predicted values of the Banks-Indicative Opening Euro Rates – Selling for the first quarter of year 2011 with their corresponding differences.

Table 4.9: Actual and Predicted Banks-Indicative Opening Euro Rates – Selling

Date	Actual Rate	Predicted Rate	Difference
Friday 7th January 2011	1.9107	1.9381	0.0274
Friday 14th January 2011	1.9829	1.9875	0.0046
Friday 21th January 2011	2.0018	2.0214	0.0196
Friday 28th January 2011	2.0468	2.0711	0.0243
Friday 4th February 2011	2.0948	2.0971	0.0023
Friday 11th February 2011	2.0776	2.099	0.0214
Friday 18th February 2011	2.0775	2.0991	0.0216
Friday 25th February 2011	2.1141	2.1352	0.0211
Friday 4th March 2011	2.1346	2.1601	0.0255
Friday 11th March 2011	2.116	2.1281	0.0121
Friday 18th March 2011	2.157	2.1686	0.0116
Friday 25th March 2011	2.1761	2.1983	0.0222

Table 4.4.10: Paired Samples Statistics – Euro

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	Actual	2.074158	12	.0773035	.0223156
	Predicted	2.091967	12	.0769453	.0222122

As we can observe from table 4.10 the predicted mean rate (2.091967) is slightly higher than the actual mean rate (2.074158).

Considering table 4.4.11 we can deduce that there is a strong positive correlation between the actual Banks-Indicative Opening Euro Rates – Selling and the predicted Banks-Indicative Opening Euro – Selling. This is realistic from the correlation value .994.

Table 4.4.11: Paired Samples Correlations – Euro

		N	Correlation	Sig.
Pair 1	Actual & Predicted	12	.994	.000

The Paired Samples T Test used compares the means of actual and predicted Banks-Indicative Opening Euro – Selling. It computes the difference between the two variables for each case, and tests to see if the average difference is significantly different from zero. From Table 4.4.12 we realize the descriptive statistics for the difference between the actual and predicted Banks-Indicative Opening Euro Rates – Selling.

Table 4.12: Paired Samples Test - Euro

	Paired Differences					t	df	Sig. (2-tailed)
				95% Confidence Interval of the Difference				
	Mean	Std. Deviation	Std. Error Mean	Lower	Upper			
Pair 1 Actual - Predicted	-.0178083	.0082020	.0023677	-.0230197	-.0125970	-7.521	11	.000

The t value is -7.521 with 11 degrees of freedom (df) presenting a significance value of .000 for the 2-tailed test. In view of the fact that the significance value is less than .05, there is no significant difference between the actual and predicted Banks-Indicative

Opening Euro Rates – Selling. In conclusion, we can therefore say that at 95% confidence interval of the difference the prediction is very close to the actual.

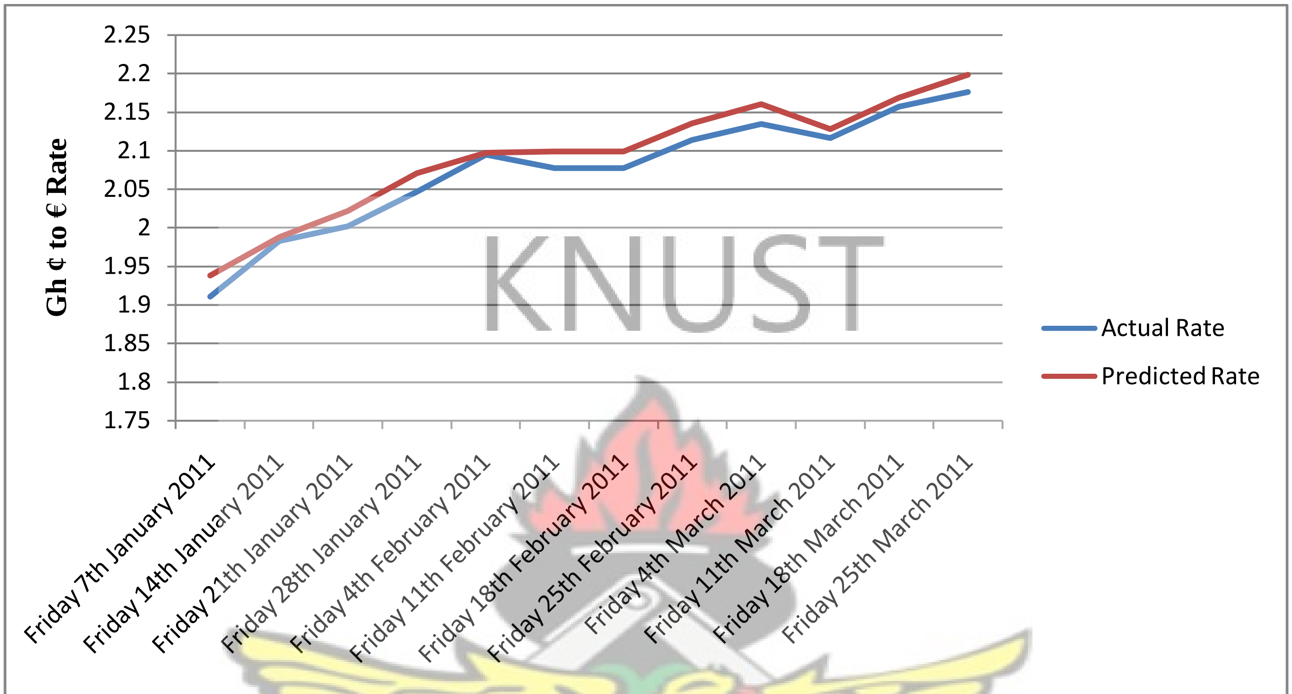


Figure 4.10: Line graph of Actual and Predicted rates – Euro

Figure 4.4.10 and Figure 4.11 show the graphical presentation of the actual and predicted Banks-Indicative Opening Euro Rates – Selling for the first quarter of the year 2011. The two graphs, both those with line representation and the bar validate the closeness of the predicted values to the actual values.

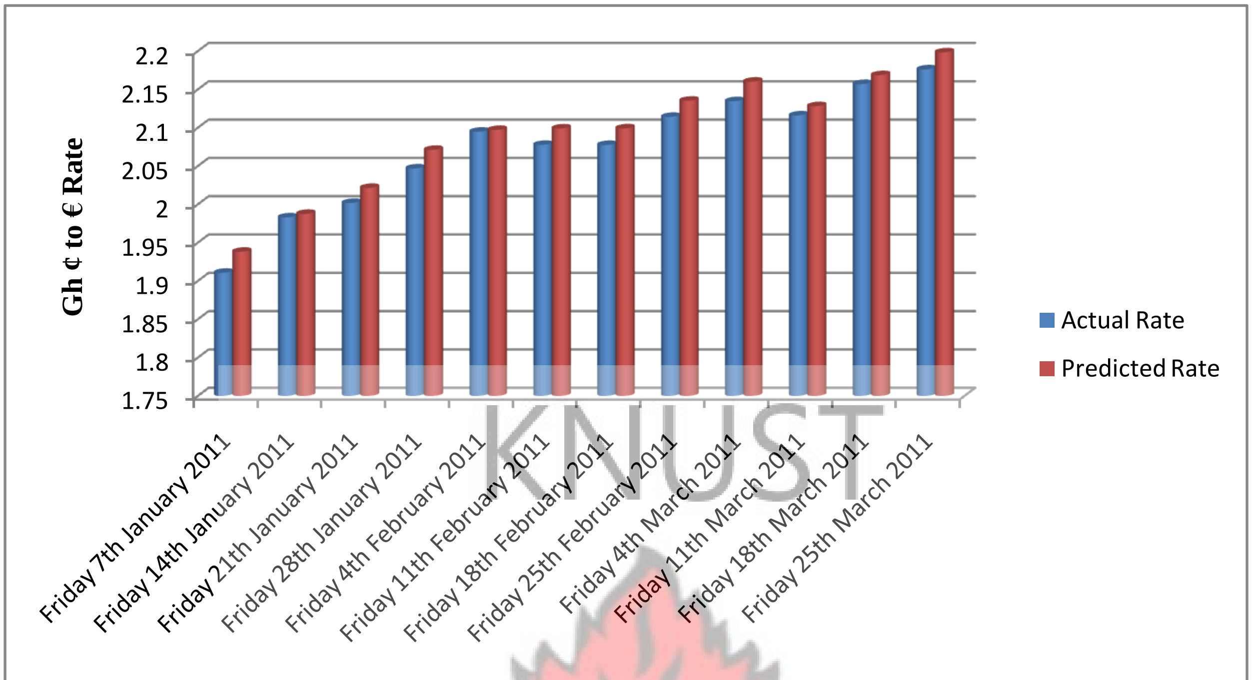


Figure 4.11: Bar graph of Actual and Predicted rates – Euro

Comparing the predictions of the three currencies (US Dollars, Pound Sterling and Euro) under study, we can clearly deduce that the predictions of Banks-Indicative Opening Euro Rates – Selling give the most accurate values compared to the actual rate. The next accurate predictions were obtained from the Banks-Indicative Opening U.S. Dollars Rates – Selling and Banks-Indicative Opening Pound Sterling Rates – Selling given the comparatively wider difference of predicted values against the actual. These are comprehensible in the graphs produce in the statistics.

4.5 Comparison of Models

After careful consideration of the forecast values obtained, it is realized that a comparison of the improved model with the base model proposed by Faraway and Chartfield. Table 4.5 shows the comparison of the results of Banks-Indicative Opening Euro Rates – Selling obtained from the two models under study.

Table 4.5: Comparison results of Banks-Indicative Opening Euro Rates – Selling obtained from the two models under study.

Date	Actual Rate	Predicted Rate	Difference	Faraway-Chartdield Model	Difference B/n Actual & Faraway-Chartfield Model	Difference B/n Improved Model & Faraway-Chartfield Model
Friday 7th January 2011	1.9107	1.9381	0.0274	1.990453	0.079753	0.052353
Friday 14th January 2011	1.9829	1.9875	0.0046	1.996621	0.013721	0.009121
Friday 21th January 2011	2.0018	2.0214	0.0196	2.060635	0.058835	0.039235
Friday 28th January 2011	2.0468	2.0711	0.0243	2.120837	0.074037	0.049737
Friday 4th February 2011	2.0948	2.0971	0.0023	2.101918	0.007118	0.004818
Friday 11th February 2011	2.0776	2.099	0.0214	2.143461	0.065861	0.044461
Friday 18th February 2011	2.0775	2.0991	0.0216	2.143974	0.066474	0.044874
Friday 25th February 2011	2.1141	2.1352	0.0211	2.179808	0.065708	0.044608
Friday 4th March 2011	2.1346	2.1601	0.0255	2.214532	0.079932	0.054432
Friday 11th March 2011	2.116	2.1281	0.0121	2.153704	0.037704	0.025604
Friday 18th March 2011	2.157	2.1686	0.0116	2.193621	0.036621	0.025021
Friday 25th March 2011	2.1761	2.1983	0.0222	2.246609	0.070509	0.048309
TOTAL	**24.8899**	**25.1036**	**0.2137**	**25.546173**	**0.656273**	**0.442573**
AVERAGE	***1.9146***	***1.931***	***0.0164***	***1.96509***	***0.050483***	***0.034044***

From Table 4.5, the average difference of the predicted values of the improved model is 0.0164 whereas the average difference of the predicted values from Faraway and Chartfield model is 0.050483. Consequently, Faraway and Chartfield model seem to produce 0.034044 higher than the improved model with reference to the average difference of the predictions. Figure 4.12 below display the graph of the actual and the predictions of both models.

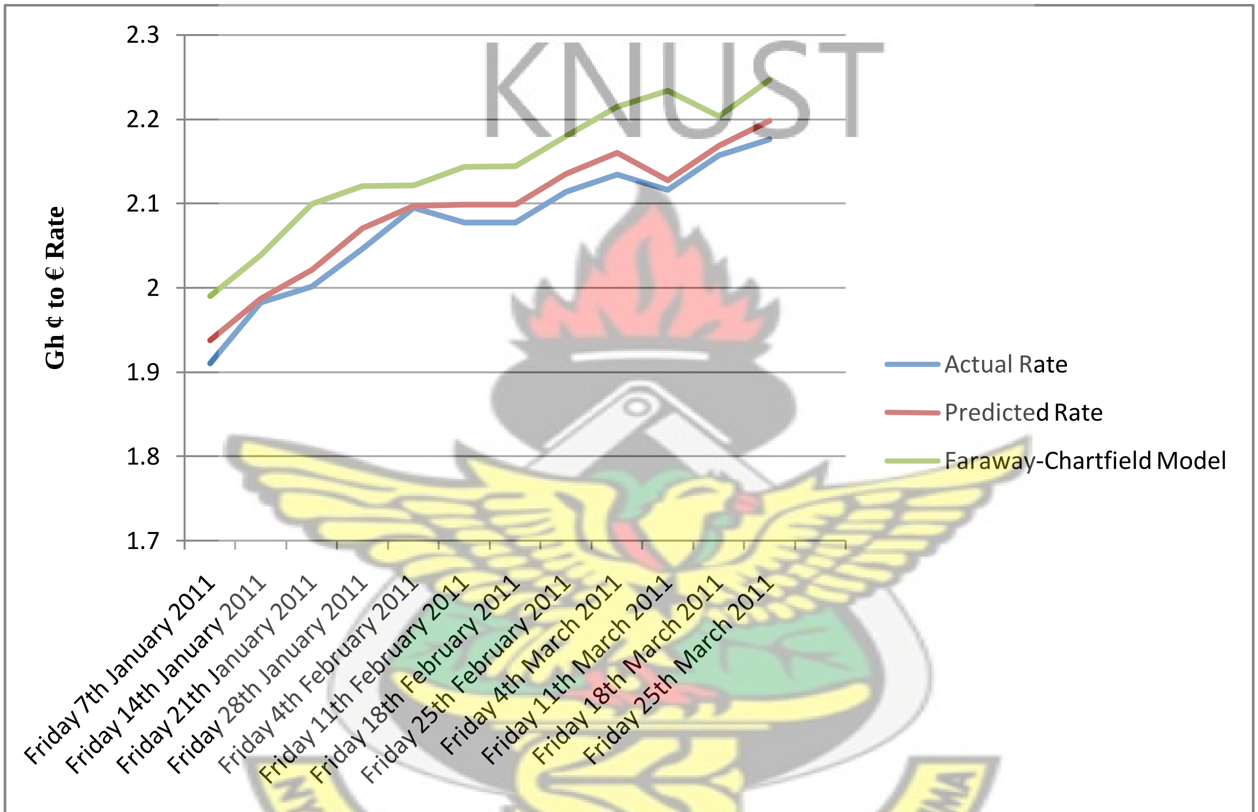


Figure 4.12 Line graphs of the actual and the predictions of both models.

It can therefore be inferred that though Faraway and Chartfield model is a good prediction model, it is suitable for the airline data (a non categorical data) than foreign exchange rate predictions. We can conclude that the improved model works more effectively in the prediction of foreign exchange rate which is considered to be a categorical data.

CHAPTER FIVE: CONCLUSIONS

5.0 Summary and Conclusion

The pertinent view, in economic literature, that exchange rates follow a random walk, has been dismissed by recent empirical work. There is now strong evidence that exchange rate returns are not independent of past changes.

This is because a review of various practical applications and papers written on applications of neural network in financial market succeeds by producing very significantly close predictions. It has been realized that one of the most important features of a neural network is its ability to adapt to new environments.

There are many different types of Neural Networks, each of which has different strengths particular to their applications.

In our application of Neural Network in Financial Market we use a particularly popular algorithm called the "feedforward" to forecast Ghana's Banks-Indicative Opening Rates. The feedforward algorithm proceeds as follows. First, inputs (Banks-Indicative Opening Rates) are passed forward to the hidden layer and multiplied by their respective rates to compute a rated sum. Next, the rated sum is modified by a transfer function (usually a logistic -- or sigmoid -- function) and then sent to the output layer. Third, the output layer neuron re-calculates the rated sum and applies the transfer function to produce the output value of this forward pass. Finally, an error signal, which is computed as the difference between the output value of the forward pass and the target value, is "feedforward" to the hidden layer and then to the input layer. Every rate that connects the hidden and output layers is adjusted proportionally to each neuron's contribution to the forecast error with the objective to minimize the mean squared-error.

It is natural and informative to judge forecasts by their accuracy. However, actual and forecasted values will differ, even for very good forecasts.

In our forecast, the predictions gave results which are considered as very significantly close marginal differences. The forecast values of the US Dollar exchange rate produced differences in the range of 0.01 and 0.03. This result is obtained from several tests performed by using different input based on past data from Bank of Ghana, the Bank Indicative Opening Rates.

Upon comparison the average difference of the predicted values of the improved model is 0.0164 whereas the average difference of the predicted values from Faraway and Chartfield model is 0.050483. Consequently, Faraway and Chartfield model seem to produce 0.034044 higher than the improved model with reference to the average difference of the predictions.

It can therefore, be concluded that application of neural network – feed foreward neural network with three neurons in financial market is a good model for forecasting Ghana's Exchange Rates.

5.1 Recommendations

Obviously, the Application of Neural Network as a whole and partly in Financial Market is a very broad. Although much has been done in this area since it has been a major interested research area for not only Computer Scientist or Scientists in general but also by Business and other disciplines, it is by no means exhaustive. Hence there is the need for recommendations for future improvements.

- This research considered the application of neural network in financial market in Ghana and specifically concentrated on the forecast of exchange rate and narrowed it down to predicting the future values of only three foreign currencies.

It can therefore, be extended to predict the future values of the other foreign currencies which Ghana trades in.

- It is also possible that the forecast can be extended to cover predictions of other financial securities such as treasury bills, bonds and shares to aid traders and investors to make projections.

- In this research, the model of the neural network was restricted to a single hidden layer, but it is possible to have multiple layered neural network structure. This will make the structure a bit complicated and increase the time the learning algorithm will converge at a minimum result. But we can foresee that it will produce more accurate results.

- Although, there are different types of neural networks of which this research centers on one of the popular ones, “feedforward” neural network. We can be sure that each type has different dimension of operation. We therefore recommend that multiple types of neural network be used which is possible to produce more accurate results.

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